Pain at the Pump: The Effect of Gasoline Prices on New and Used Automobile Markets*

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Abstract

We estimate the effect of gasoline prices on short-run equilibrium prices, market shares, and sales of new and used cars of different fuel economies. We find that gasoline prices have larger effects on the prices of used cars than of new cars, but that they have large effects on market shares and sales of new cars. We use our findings to investigate whether consumers are myopic about future gasoline costs when they buy cars, and to investigate how market structure can influence the effect of environmental policies.

1 Introduction

According to EPA estimates, gasoline combustion by passenger cars and light-duty trucks is the source of about fifteen percent of U.S. greenhouse gas emissions, "the largest share of any end-use economic sector."[1] As public concerns about climate change grow, so does interest in designing policy instruments that will reduce carbon emissions from this source. In order to be effective, any such policy must reduce gasoline consumption, since carbon emissions are essentially proportional to the amount of gasoline used. The major policy instrument that has been used so far to influence gasoline consumption in the U.S. has been the Corporate Average Fuel Efficiency (CAFE) standards (Goldberg (1998), Jacobsen (2010)). Some economists, however, contend that changing the incentives to use gasoline—by increasing its price—would be a preferable approach. This is because changing the price of gasoline has the potential to influence both what cars people buy and how much people drive.

This paper addresses two questions that are crucial for assessing whether a gasoline price related policy instrument (such as an increased gasoline tax or a carbon tax) could influence what cars people buy. The first key question is how sensitive consumers are to expected future gasoline costs when they make new car purchases. More precisely, how much does an increase in the price of gasoline affect the willingness-to-pay of consumers for cars of different fuel economies? If consumers are very myopic, meaning that their willingness-to-pay for a car is little affected by changes in the expected future fuel costs of using that car, then a gasoline price instrument will not influence their choices very much and will not be sufficient to achieve the first-best outcome in the presence of an externality. One might think of this loosely as the "demand side" determinant of the effectiveness of such a policy.[2]

There is also a "supply side" determinant. Consumer myopia determines how much a change in the price of gasoline will change the demand for different kinds of cars. Whether the resulting change in *demand* will change which cars consumers buy *in equilibrium* depends on the market structure of the car market itself. In a competitive car market with very inelastic supply, a change in the demand for a particular type of car would affect the equilibrium price of that type of car by a lot, but the equilibrium quantity very little. Alternatively, a car manufacturer with market power could adjust the prices of different types of cars in order to counteract the effect of gasoline price changes.[3] In both these scenarios, a policy-induced change in gasoline prices would have little

[1]EPA, Inventory of U.S. Greenhouse Gas Emissions and Sinks: 1990-2006, p. 3-8.

[2]This condition is not unique to the case of gasoline consumption. Hausman (1979) was the first to investigate whether consumers are myopic when purchasing durable goods that vary in energy costs. More generally, this is an example of the quite obvious point that a policy must influence something that consumers pay attention to in order to actually affect the choices consumers make.

[3]In 2006, GM directly counteracted the effect of gasoline prices for buyers of its largest cars and SUVs. GM

effect on what cars were purchased in equilibrium. Conversely, in a competitive market with an elastic supply curve, or in a market in which oligopolist manufacturers offered little price response, a gasoline price change could have a larger effect on what cars are purchased. Understanding the market structure of the target market is therefore also key to understanding the effects of a policy intervention.

Our analysis proceeds in three steps. First, we estimate how the price of gasoline affects market outcomes in both new and used car markets. Specifically, we use data on individual transactions for new and used cars to estimate the effect of gasoline prices on equilibrium transaction prices, market shares, and sales for new and used cars of different fuel economies. These estimates become the building blocks for our next two steps.

In our second step, we use the estimated effect of gasoline prices on prices and quantities in new and used car markets to learn about how consumers trade off the up-front capital cost of a car and the ongoing usage cost of the car. We estimate a range of implied discount rates under a range of assumptions about demand elasticities, vehicle miles travelled, and vehicle survival probabilities. We find little evidence that consumers "undervalue" future gasoline costs when purchasing cars. The implied discount rates we calculate correspond reasonably closely to interest rates that customers pay when they finance their car purchases.

In our third step, we compare our price and quantity results for new car and used car markets and discuss the reasons for the differences. The effects of gasoline prices on car prices and quantities are very different in new and used markets. We find that a \$1 change in the gasoline price is associated with a very large change in relative prices of *used* cars of different fuel economies—a difference of \$1,945 in the relative price of the highest fuel economy and lowest fuel economy quartile of cars. For *new* cars, the predicted relative price difference is much smaller—a \$354 difference between the highest and lowest fuel economy quartiles of cars. However, we find a large change in the market shares of new cars when gasoline prices change. A \$1 increase in the gasoline price leads to a 21.1% increase in the market share of the highest fuel economy quartile of cars and a 27.1% decrease in the market share of the lowest fuel economy quartile of cars. The results suggest that the industrial organization of markets does play a role in determining the effect that policy interventions which mimic price changes would have on market outcomes.

This paper proceeds as follows. In the next section, we position this paper within the related literature. In Section 3 we describe the data we use for the analysis in this paper. In Section 4 we estimate the effect of gasoline prices on equilibrium market shares, unit sales, and prices in new

issued these customers pre-paid debit cards that credited them with the difference between the average retail price of gasoline and \$1.99 for each gallon of gasoline they purchased, effectively capping the price of gasoline at \$1.99 for these customers. ("GM offers to pay part of gasoline bill for California, Florida consumers," Automotive News, May 23, 2006) and used car markets. In Section 5 we use the results estimated in Section 4 to investigate whether consumers are myopic, meaning whether they undervalue expected future fuel costs relative to the up-front prices of cars of different fuel economics. In Section 6 we compare how gasoline prices affect outcomes in new and used markets differently. Section 7 checks the robustness of our estimated results. Section 8 offers some concluding remarks.

2 Related literature

There is no single, simple answer to the question "How do gasoline prices affect gasoline usage?," and, consequently, no single, omnibus paper that answers the entire question. This is because there are many margins over which drivers, car buyers, and automobile manufacturers can adjust, each of which will ultimately affect gasoline usage. Some of these adjustments can be made quickly; others are much longer run adjustments.

For example, in the very short run, when gasoline prices change, drivers can very quickly begin to alter how much they drive. Donna (2010), Goldberg (1998), and Hughes, Knittel, and Sperling (2008) investigate three different measures of driving responses to gasoline prices. Donna investigates how public transportation utilization is affected by gasoline prices, Goldberg estimates the effect of gasoline prices on vehicle miles travelled, and Hughes *et al.* investigate monthly gasoline consumption.

At the other extreme, in the long run, automobile manufacturers can change the fuel economy of automobiles by changing the underlying characteristics—such as weight, power, and combustion technology—of the cars they sell or by changing fuel technologies to hybrid or electric vehicles. Gramlich (2009) investigates such manufacturer responses by relating year-to-year changes in the MPG of individual car models to gasoline prices.

This paper belongs to a set of papers that examine the question: How do gasoline prices affect the prices or sales of car models of different fuel economies? What this set of papers have in common is that they investigate the effect of gasoline prices on car prices, sales, or market shares, taking as given the set of cars currently available from manufacturers. This is a short-run effect, although a longer run response than the immediate changes in driving behavior. Within this set of papers there are some papers that study the effect of gasoline prices on car quantities and some that study the effect of gasoline prices on car prices.[4]

[4]There is a very large literature (reaching back almost half a century) that has investigated the effect of gasoline prices on car choices, the car industry, vehicles miles travelled, and that has estimated the elasticity of demand for gasoline. In addition to the papers described in detail in the next section, other related papers include Blomqvist and Haessel (1978), Carlson (1978), Ohta and Griliches (1986), Greenlees (1980), Sawhill (2008), Tishler (1982), and West (2007).

2.1 Gasoline prices and car quantities

Two noteworthy papers that address the effect of gasoline prices on car quantities are Klier and Linn (forthcoming) and Li, Timmins, and von Haefen (2009). Although the two papers address similar questions, they use different data. Klier and Linn estimate the effect of national average gasoline prices on national sales of new cars by detailed car model. They find that increases in the price of gasoline reduce sales of low-MPG cars relative to high-MPG cars. Li, Timmins, and von Haefen also use data on new car sales, but to this they add data on vehicle registrations, which allows them to estimate the effect of gasoline price on the outflow from, as well as inflow to, the vehicle fleet. They find differential effects for cars of different fuel economies: a gasoline price increase increases the sales of high fuel economy new cars and the survival probabilities of high fuel economy used cars, while decreasing the sales of low fuel economy new cars and the survival probabilities of low fuel economy used cars.

2.2 Gasoline prices and car prices

There are several papers that investigate whether the relationship between car prices and gasoline prices indicates that car buyers are myopic about future usage costs when they make car buying decisions.

Kahn (1986) uses data from the 1970s to relate a used car's price to the discounted value of the expected future fuel costs of that car. He finds that used car prices do adjust to gasoline prices, by about one-third to one-half the amount that would fully reflect the change in the gasoline cost. This, he concludes, indicates some degree of myopia. Kilian and Sims (2006) repeat Kahn's exercise, with a longer time series, more granular data, and a number of extensions. They conclude that buyers have asymmetric responses to gasoline price changes, responding nearly completely to gasoline price increases, but very little to gasoline price decreases.

Allcott and Wozny (2011) address this question using pooled data on both new and used cars. They also find that car buyers undervalue fuel costs. According to their estimates, consumers equally value a $1 change in the purchase price of a vehicle and a 72-cent change in the discounted expected future gasoline costs for the car. These estimates imply less myopia than do those of Kahn (1986), although still not full adjustment.

Sallee, West, and Fan (2009) carry out a similar exercise as the papers above, also relating the price of used cars to a measure of discounted expected future gasoline costs. Their paper differs from others in that it controls very flexibly for odometer readings. This means that the identifying variation they use is differences between cars of the same make, model, model year, trim, and engine characteristics, but of different odometer readings. They find that car buyers adjust to

80-100% of the change in fuel costs, depending on the discount rate used.

Verboven (1999) implements a similar approach to the papers described above but using data on European consumers' choices to buy either a gasoline- or a diesel-powered car. This choice also involves a trade-off between the upfront price for a car and the car's future fuel cost, but with variation over different fuels rather than over time in the price of a single fuel. He estimates implied discount rates between 5 and 13 percent, a range that is comparable to contemporaneous interest rates.

Goldberg (1998) approaches the question of consumer myopia in a completely different way. She calculates the elasticity of demand for a car with respect to its purchase price and with respect to its fuel cost. After adjusting the terms to be comparable, she finds that the two semi-elasticities are very similar, leading her to conclude that car buyers are not myopic.

2.3 Differences from the previous literature

Our paper differs from the papers described above in three ways. First, our paper uses data on individual new and used car transactions, rather than data from aggregate sales figures, from registrations, or from surveys. Second, our data allow us to compare the effects of gasoline prices on both prices and quantities of cars, and in both used and new markets, in data from a single data source. Third, we choose to use more flexible functional forms than many (although not all) of the papers above.

Transactions data: As described in more detail in Section 3, we observe individual transactions, and observe a variety of characteristics about each transaction, such as location, purchase timing, detailed car characteristics, and demographic characteristics of buyers. This allows us to use extensive controls in our regressions, reducing the chances that our results arise from selection issues or aggregation over heterogeneous regions, time periods, or car models.

Single data source: Using transactions-based data means that we observe prices and quantities for new and used cars in a single data set. This enables us to do several things. First, we can investigate whether the finding of no myopia by Goldberg (1998) in *new* cars differs from the finding of at least some myopia in *used* cars by Kahn (1986), Kilian and Sims (2006), and Allcott and Wozny (2011) because the effect is actually different for new and used cars, or for some other reason. Second, this enables us to learn about the industrial organization of new and used car markets, and specifically about how the differences in market structure might lead to differences in how a policy intervention would play out in the two markets.

Flexible specification: In addressing the question of myopia, researchers face a choice. The theoretical object to which customers should be responding is the present discounted value of the expected future gasoline cost for the particular car at hand. Creating this variable means having data on (or making assumptions about) how many miles the owner will drive in the future, the miles per gallon of the particular car, the driver's expectation about future gasoline prices, and the discount rate. Having constructed this variable, a researcher can then estimate a single parameter that measures the extent of consumer myopia. The advantage of estimating a structural parameter such as this is that it can be used in policy simulations or counterfactual simulations (as Li, Timmins, and von Haefen (2009), Allcott and Wozny (2011), and Goldberg (1998) do). The disadvantage is that the specific assumptions the researcher has made are "baked into" the data, and thereby into the results. It is not possible to ask how the researcher's conclusions would differ if an assumption were different without having access to the researcher's data and redoing the analysis. Furthermore, insofar as these assumptions are not correct, attenuation bias will bias the coefficients towards myopia.

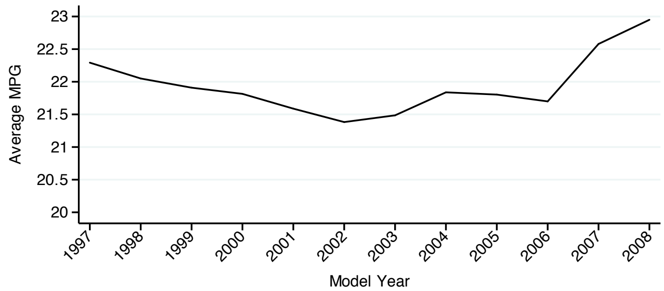
We choose to estimate more flexible, non-structural parameters. These cannot be used as structural parameters in policy simulations or counterfactuals. We argue that the results are nevertheless inputs into very informative back-of-the-envelope calculations, and furthermore, calculations that a reader of this paper can replicate for him- or herself with alternative assumptions about driving behavior, discount rates, or vehicle life.

3 Data

We combine several types of data for the analysis. Our main data contain information on automobile transactions from a sample of about 20% of all new car dealerships in the U.S. from January 1, 1999 to June 30, 2008. The data were collected by a major market research firm, and include every new car and used car transaction within the time period that occurred at the dealers in the sample. For each transaction we observe the exact vehicle purchased, the price paid for the car, information on any vehicle that was traded in, and (Census-based) demographic information on the customer. We discuss the variables used in each specification later in the paper.

We supplement these transaction data with data on car models' fuel consumption and data on gasoline prices. We measure each car model's fuel economy with the Environmental Protection Agency (EPA)'s "Combined Fuel Economy" which is a weighted geometric average of the EPA Highway (45%) and City (55%) Vehicle Mileage. As shown in Figure 1, the average MPG of models available for sale in the United States declined slowly in the first part of our sample period,

Figure 1: Average MPG of available cars by model year



then increased in the latter part.[5] Overall, however, the average MPG of available models (not sales-weighted) stays between about 21.5 and 23 miles per gallon for the entire decade.[6]

We also used gasoline price data from OPIS (Oil Price Information Service) which cover the same time period. OPIS obtains gasoline price information from credit card and fleet fuel card "swipes" at a station level. We purchased monthly station-level data for stations in 15,000 ZIP codes. Ninety-eight percent of all new car purchases in our transaction data are made by buyers who reside in one of these ZIP codes.

We aggregate the station-level data to obtain average prices for basic grade gasoline in each local market, which we define as Nielsen Designated Market Areas, or "DMAs" for short. There are 210 DMAs. Examples are "San Francisco-Oakland-San Jose, CA," "Charlotte, NC," and "Ft. Myers-Naples, FL." We aggregate station-level data to DMAs instead of to ZIP-codes for two reasons. First, we only observe a small number of stations per ZIP-code, which may make a ZIP-code average prone to measurement error.[7] Second, consumers are likely to react not only to the gasoline prices in their own ZIP-code but also to gasoline prices outside their immediate neighborhood. This is especially true if price changes that are specific to individual ZIP-codes are transitory in nature. Later we investigate the sensitivity of our results to different aggregations of gasoline prices (see section 7.4).

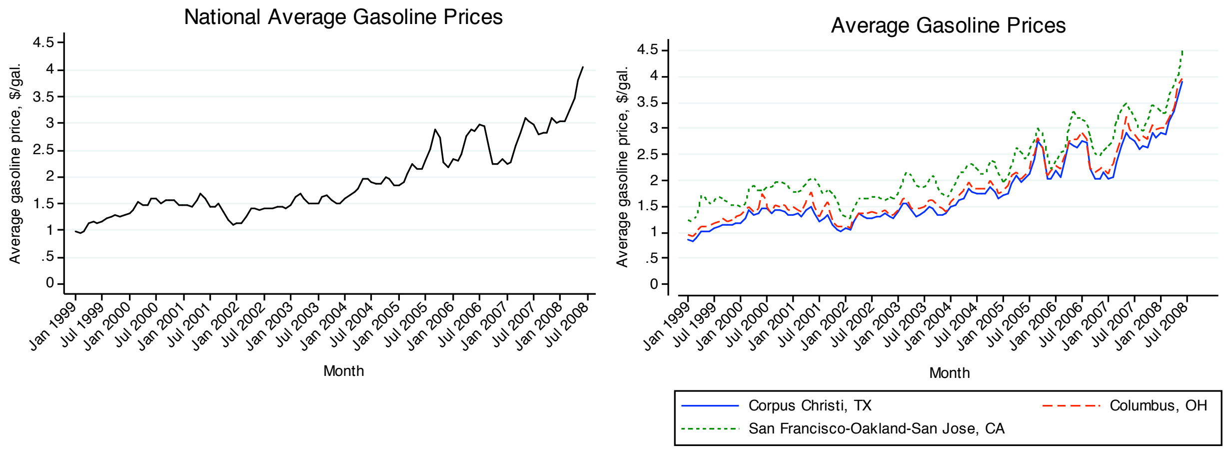
Figure 2 gives a sense of the variation in the gasoline price data. The left panel graphs monthly national average gasoline prices and shows substantial intertemporal variation within our sample period; between 1999 and 2008, average national gasoline prices were as low as $1 and as high as

[5] In 2008, the EPA changed how it calculates MPG. In this figure, the 2008 data point has been adjusted to be consistent with the EPA's previous MPG formula.

[6] While *vehicles* changed fairly little in terms of average fuel economy over this period, this does not mean that there was no improvement in technology to make *engines* more fuel-efficient. The average horsepower of available models increased substantially over the sample years, a trend that pushed toward higher fuel consumption, working against any improvements in fuel efficiency technology. See Knittel (2009) for a discussion of these issues and estimates of the rate of technological progress over this time period.

[7] In our data, the median ZIP code reports data from 3 stations on average over the months of the year. More than 25% of ZIP-codes have only one station reporting.

Figure 2: Monthly average gasoline prices (national and by DMA)



$4. While gasoline prices were generally trending up during this period there are certainly months where gasoline prices fall.

There is also substantial regional variation in gasoline prices. The right panel of Figure 2 illustrates this by comparing three DMAs: Corpus Christi, TX; Columbus, OH; and San Francisco-Oakland-San Jose, CA. California gasoline prices are substantially higher than prices in Ohio (which are close to the median) and Texas (which are low). While the three series generally track each other, in some months the series are closer together and in other months they are farther apart, reflecting the cross-sectional variation in the data.

To create our final dataset, we draw a 10% random sample of all transactions.[8] After combining the three datasets this leaves us with a new car dataset of 1,863,403 observations and a used car dataset of 1,096,874 observations. Table 11 presents summary statistics for the two datasets.

4 Estimation and results

In this section we estimate the short-run equilibrium effects of changes in gasoline prices on the transaction prices, market shares, and unit sales of cars of different fuel economics. We separate our analysis by new and used markets. We will use the results estimated in this section to investigate, in Section 5, whether car buyers "undervalue" future fuel costs and in Section 6 to discuss how differences in market structure can influence the effects of environmental policies.

[8]The 10% sample is necessary to allow for estimation of specifications with multiple sets of high-dimensional fixed effects, including fixed effect interactions, that we use later in the paper.

4.1 Specification and variables for car price results

At the most basic level, our approach is to model the effect of covariates on short-run equilibrium price and (in the next subsection) quantity outcomes. For the car industry, the short-run horizon is several months to a few years. During this time frame, a manufacturer can alter both price and production quantities, but its offering of models is pre-determined, its model-specific capacity is largely fixed, and a number of input arrangements are fixed (labor contracts, in particular). While some of these aspects become more flexible over a year or two (models can be tweaked, some capacity can be altered), only over a long-run horizon (four years or more), can a manufacturer introduce fundamentally different models into its product offering.

We use a reduced form approach. In completely generic terms, this means regressing observed car prices (P) on demand covariates (X^D) and supply covariates (X^S):

$$P = \alpha_0 + \alpha_{\mathbf{1}}\mathbf{X^D} + \alpha_{\mathbf{2}}\mathbf{X^S} + \nu \tag{1}$$

The estimated $\hat{\alpha}$'s we obtain from this specification estimate neither parameters of the demand curve nor of the supply curve, but instead estimate the effect of each covariate on the equilibrium P, once demand and supply responses are both taken into account.

Our demand covariates are gasoline prices (the chief variable of interest), customer demographics, and variables describing the timing of the purchase, all described in greater detail below. We also include region-specific year fixed effects, region-specific month-of-year fixed effects, and detailed "car type" fixed effects. Supply covariates should presumably reflect costs of production of new cars (raw materials, labor, energy, etc.). We suspect that these vary little within the region-specific year and region-specific month-of-year fixed effects that are already included in the specification. Furthermore, our interactions with executives responsible for short- to medium-run manufacturing and pricing decisions for automobiles indicate that, in practice, these decisions are not made on the basis of small changes to manufacturing costs.

We can write the specification we estimate more precisely as:

$$\begin{aligned} P_{irjt} = \lambda_0 + \lambda_{\mathbf{1}}(\text{GasolinePrice}_{it} \cdot \text{MPG Quartile}_j) + \lambda_{\mathbf{2}}\mathbf{Demog}_{it} + \\ \lambda_{\mathbf{3}}\mathbf{PurchaseTiming}_{jt} + \delta_j + \tau_{rt} + \mu_{rt} + \epsilon_{ijt}. \end{aligned} \tag{2}$$

The price variable recorded in our dataset is the pre-sales-tax price that the customer pays for the vehicle, including factory installed accessories and options, and including any dealer-installed accessories contracted for at the time of sale that contribute to the resale value of the car.[9]

[9] Dealer-installed accessories that contribute to the resale value include items such as upgraded tires or a sound system, but would exclude options such as undercoating or waxing.

We make two adjustments in order to make P_{irjt} capture the customer's total wealth outlay for the car. First, we subtract off the manufacturer-supplied cash rebate to the customer if the car is purchased under a such a rebate, since the manufacturer pays that amount on the customer's behalf. Second, we subtract from the purchase price any profit or add to the purchase price any loss the customer made on his or her trade-in. Dealers are willing to trade off profits made on the new vehicle transaction and profits made on the trade-in transaction, including being willing to lose money on the trade-in.[10] If a customer loses money on the trade-in transaction, part of his or her payment for the new vehicle is an in-kind payment with the trade-in vehicle. By adding such a loss to the negotiated (contract) price we adjust the price to include the value of this in-kind payment. In Equation 2, P_{irjt} is the above-defined price for transaction i in region r on date t for car j.

We estimate how gasoline prices affect the transaction prices paid for cars of different fuel economies. One might think that higher gasoline prices, by making car ownership more expensive, should lead to lower negotiated prices for all cars. Note, however, that cars do not increase uniformly in fuel cost: a compact car has lower fuel costs than an SUV at every gasoline price, but as gasoline price rises, its fuel cost advantage *relative* to the SUV actually *rises*. If enough people continue to want to own cars, even when gasoline prices increase, then higher gasoline prices may lead to increased demand for high fuel economy cars and decreased demand for low fuel economy cars, and consequently to the transaction price rising for the highest fuel economy cars and falling for the lowest fuel economy cars. To capture this, we estimate separate coefficients for the *GasolinePrice* variable depending on the fuel economy quartile into which car j falls. Specifically, we classify all transactions in our sample by the fuel economy quartile (based on the EPA Combined Fuel Economy MPG rating for each model) into which the purchased car type falls.[11] Quartiles are re-defined each year based on the distribution of all models *offered* (as opposed to the distributions of vehicles sold) in that year. Table A-1 reports the quartile cutoffs and mean MPG within quartile for all years of the sample.

We use an extensive set of controls. First, we control for a wide range of demographic variables ($Demog_{it}$) using data from the 2000 Census: income, house value and ownership, household size, vehicles per household, education, occupation, average travel time to work, English proficiency, and race of buyers.[12] We use data at the level of "block groups," which, on average, contain about 1100 people. We also control for a series of variables that describe purchase timing ($PurchaseTiming_{jt}$): *EndOfYear* is a dummy variable that equals 1 if the car was sold within the last 5 days of the

[10] See Busse and Silva-Risso (2010) for further discussion of this.

[11] We obtain similar results if we estimate four separate regressions, thereby relaxing the constraint that the parameters associated with the other covariates are equal across fuel economy quartiles.

[12] Demographic variables do not change over time in our data.

year; *EndOfMonth* is a dummy variable that equals 1 if the car was sold within the last 5 days of the month; *WeekEnd* is a dummy variable that specifies whether the car was purchased on a Saturday or Sunday. If there are volume targets or sales on weekends or near the end of the month or the year, we will absorb their effects with these variables. For new cars, $PurchaseTiming_{jt}$ includes fixed effects for the difference between the model year of the car and the year in which the transaction occurs. This distinguishes between whether a car of the 2000 model year, for example, was sold in calendar 2000 or in calendar 2001. For used cars, $PurchaseTiming_{jt}$ includes a flexible function of the car's odometer, described in more detail below, which controls for depreciation over time.

We include year, τ_{rt}, and month-of-year, μ_{rt}, fixed effects corresponding to when the purchase was made. Both year and month-of-year fixed effects are allowed to vary by the geographic region (34 throughout the U.S.) in which the car was sold.[13] The identifying variation we use is therefore variation within a year and region that differs from the average pattern of seasonal variation within that region.[14] To examine the robustness of our results to which components of variation in the data are used to identify the effect of gasoline prices, we repeat our estimation with a series of different fixed effect specifications in Section 7.1. We also control for detailed characteristics of the vehicle purchased by including "car type" fixed effects (δ_j). A "car type" in our sample is the interaction of make, model, model year, trim level, doors, body type, displacement, cylinders, and transmission. (For example, one "car type" in our data is a 2003 Honda Accord EX 4-door sedan with a 4-cylinder 2.4-liter engine and automatic transmission.)

Before describing the results, we note that our estimates should be interpreted as estimates of the short-run effects of gasoline prices, meaning effects on prices, market shares, or sales over the time horizon in which manufacturers would be unable to change the configurations of cars they offer in response to gasoline price changes, a period of several months to a few years. Persistently higher gasoline prices would presumably cause manufacturers to change the kinds of vehicles they choose to produce, as U.S. manufacturers did in the 1970s at the time of the first oil price shock.[15] The nature of our data, its time span, and our empirical approach are all unsuited to estimating what the long-run effects of gasoline price would be on prices or sales. The short-run estimates are nevertheless useful, we believe, for two reasons. First, the short run effect is indeed the effect we want to estimate in order to investigate the question of consumer myopia. More generally,

[13] See Table A-19 for a list of regions and the DMAs within each region.

[14] The average price of gasoline in a DMA-month (our unit of observation) is \$1.91; the standard deviation is 0.68. The "within-region" standard deviation is 0.21, a value that is 11% of the mean. The "between-region" standard deviation is 0.72. (The "within" standard deviation is the standard deviation of $X_{DMA,month} - \bar{X}_{region,year} + \bar{X}$ where $\bar{X}_{region,year}$ is the average for the region-year and $\bar{X}$ is the global mean. The between standard deviation is the standard deviation of $\bar{X}_{region,year}$.)

[15] As gasoline prices began to fall in the early 1980s, CAFE standards also affected manufacturer offerings.

short-run effects are important for auto manufacturers in the short-to-medium term (especially if financial solvency is an issue) and because they yield some insight into the size of the pressures to which manufacturers are responding as they move towards the long run.

4.2 New car price results

We first estimate Equation 2 using data on new car transactions. The full results from estimating this specification are presented in Table A-2. The variable of primary interest is *GasolinePrice* in month t in the DMA in which customer i resides.[16] This variable is interacted with an indicator variable which equals 1 if the observation is for cars in MPG quartile k. The coefficients of interest are the four coefficients in the vector $\lambda_{\mathbf{1}}$ which represent the effect of gasoline prices on the prices of cars in each of the four MPG quartiles; these coefficients and their standard errors are reported in Table 1.[17]

Table 1: Gasoline price coefficients from new car price specification

Variable	Coefficient	SE
GasolinePrice*MPG Quart 1 (lowest fuel economy)	-250**	(72)
GasolinePrice*MPG Quart 2	-96**	(37)
GasolinePrice*MPG Quart 3	-11	(26)
GasolinePrice*MPG Quart 4 (highest fuel economy)	104**	(47)

These estimates indicate that a $1 increase in the price of gasoline is associated with a lower negotiated price of cars in the lowest fuel economy quartile (by $250) but a higher price of cars in the highest fuel economy quartile (by $104), a relative price difference of $354. Overall, the change in negotiated prices appears to be monotonically related to fuel economy. Note that this is an equilibrium price effect; it is the net effect of the manufacturer price response, any change in consumers' willingness-to-pay, and the change in the dealers' reservation price for the car.[18]

4.3 Used car price results

In this section, we estimate the effect of gasoline prices on the transaction prices of used cars by estimating Equation 2 (with some modifications) using the data on used car transactions. We observe all the same car characteristics for used cars that we do for new cars, enabling us to use all the covariates to estimate the used car price results that we used to estimate the results for

[16] Another approach would be to use a variable that represents gasoline price expectations, perhaps based on futures prices for crude oil. In section 7.2 we explore such an approach.

[17] Two asterisks (**) signifies significance at the .01 level, * signifies significance at the .05 level and + at the .10 level.

[18] In previous versions, we estimated Equation 2 separately for different vehicle segments (such as compact, midsize, SUV, etc.). These results are available from the authors.

new cars, including identical "car type" fixed effects. However, there is one important difference between used cars and new cars. A new car of a given model-year can sell only during that model-year; a used car of a given model-year can sell in many different years. Over that time period, tastes may change, and individual vehicles will depreciate. To capture the effect of depreciation on used car transaction prices, we include a spline in odometer (*Odom*) when we estimate Equation 2 using the data on used car transactions.[19] The spline has knots at 10,000-mile increments, allowing a different per mile rate of depreciation for each 10,000-mile range of mileage.[20] We interact the spline with segment indicator variables to allow different types of cars to have different depreciation paths, and with indicators for five regions of the country defined by Petroleum Administration for Defense Districts (PADDs) to allow these paths to vary regionally.[21] In addition, in order to allow for changes in tastes for different vehicles segments over time, we replace the year fixed effects in Equation 2 with segment-specific year fixed effects.[22] In the new car specification (Equation 2) we allowed the year fixed effects to differ by region. We also allow the segment-specific year fixed effects to vary by geography, however, to reduce the number of fixed effects we have to estimate, we now interact the segment-specific year fixed effects with PADD instead of region.[23] This three way interaction controls for business cycle fluctuations that affect the entire car market, for year-to-year changes in tastes for different segments of cars (such as the increasing popularity of SUVs), and allows both of these effects to vary across the five PADD regions of the country. Taking into account these modifications, the specification we estimate for used cars is:

$$\begin{aligned} P_{irjt} = {} & \lambda_0 + \lambda_{\mathbf{1}}(\text{GasolinePrice}_{it} \cdot \text{MPG Quartile}_j) + f_{10{,}000}(\text{Odom}_i, \lambda_{\mathbf{2rj}}) \cdot \text{Segment}_j \cdot \text{PADD}_r \\ & + \lambda_{\mathbf{3}}\mathbf{Demog}_{it} + \lambda_{\mathbf{4}}\mathbf{PurchaseTiming}_{jt} + \delta_j + \tau_{rjt} + \mu_{rt} + \epsilon_{ijt}, \end{aligned} \tag{3}$$

where τ_{rjt} is the year-segment-PADD fixed effect.

There is one difference between new and used cars in the definition of the dependent variable. A customer who is buying a used car can use a trade-in in the transaction, just as a buyer of a new car can, so the price definition subtracts any profits (or adds any losses) the customer makes on the trade-in, just as it does for new cars. However, used cars never have customer rebates offered,

[19]In using odometer, our approach resembles Sallee, West, and Fan (2009). We differ from Allcott and Wozny (2011), who use car age to measure depreciation. We use odometer for two reasons. First we find that adding car age does very little (in an R^2 sense) to explain depreciation once odometer is accounted for. Second, since odometer varies across individual vehicles, and does not move in lockstep with calendar time, odometer is less collinear with gasoline price than car age is. Using odometer thus increases our ability to identify a gasoline price effect in the data, if there is one.

[20]We drop the 0.97% of the sample with odometer readings of 150,000 miles or greater.

[21]There are seven segments: Compact, Midsize, Luxury, Sporty, SUV, Pickup, and Van. The five PADDs are East Coast, Midwest, Gulf Coast, Rockies, and West Coast.

[22]In the new car specification, changes in tastes are captured by the car type fixed effects since any particular car type sells as a new car only for one model-year.

[23]In unreported results we find that using year-times-segment-times-region fixed effects yields very similar results.

so there is no need to subtract that amount from the reported transaction price.

As we did for new cars, we estimate the effect of gasoline prices on used car prices separately by the MPG quartile of the used car being purchased. The full results are reported in Table A-3. The gasoline price coefficients are reported in Table 2.

Table 2: Gasoline price coefficients from used car price specification

Variable	Coefficient	SE
GasolinePrice*MPG Quart 1 (lowest fuel economy)	-1182**	(42)
GasolinePrice*MPG Quart 2	-101	(62)
GasolinePrice*MPG Quart 3	468**	(36)
GasolinePrice*MPG Quart 4 (highest fuel economy)	763**	(44)

These estimates show a much larger effect on the equilibrium prices of used cars than was estimated for new cars. The estimates indicate that a $1 increase in gasoline price is associated with a lower negotiated price of cars in the lowest fuel economy quartile (by $1,182) but a higher price of cars in the highest fuel economy quartile (by $763), a relative price difference of $1,945, compared to a difference of $354 for new cars. (We will consider the reasons for these differences in Section 6.)

4.4 Specification and variables for car quantity results

In this section we estimate the reduced form effect of gasoline prices on the equilibrium market shares and sales of new cars of different fuel economies. We can write an analog of Equation 1 that gives a reduced form expression for new car quantity, or some function of quantity, as a function of demand and supply covariates:

$$Q = \beta_0 + \beta_\mathbf{1}\mathbf{X^D} + \beta_\mathbf{2}\mathbf{X^S} + \eta \tag{4}$$

As with Equation 1, the estimated $\hat{\beta}$s will measure neither parameters of the demand curve, nor parameters of the supply curve, but instead the estimated short-run effects of the covariates on equilibrium quantities.

We will estimate two variants of Equation 4. In the first variant, we will use the market shares of vehicles of different types as an outcome variable, rather than unit sales. There are two advantages to this approach. First, using market share controls for the substantial fluctuation in aggregate car sales over the year. Second, this approach enables us to control for transaction- and buyer-specific effects on car purchases. The disadvantage is that if changes in gasoline prices affect total unit sales of new cars too much, changes in market share may not correspond to changes in unit sales. In light of this, we will later estimate a second variant of Equation 4 using two different measures of unit sales.

In our market share regression we estimate the effect of gasoline prices on market shares of cars of different fuel economies using a set of linear probability models that can be written as:

$$I_{irt}(j \in K) = \gamma_0 + \gamma_1 \text{GasolinePrice}_{it} + \boldsymbol{\gamma_2}\mathbf{Demog}_{it} + \boldsymbol{\gamma_3}\mathbf{PurchaseTiming}_{jt} + \tau_{rt} + \mu_{rt} + \epsilon_{ijt}. \quad (5)$$

$I_{irt}(j \in K)$ is an indicator that equals 1 if transaction i in region r on date t for car type j was for a car in class K.[24] We use quartiles of fuel economy to define the classes into which a car type falls.[25] As described in Section 4.1, quartiles are based on the distribution of fuel economies of car models for sale in a given year (i.e., the model-weighted, not sales-weighted, distribution).

The variable of primary interest is *GasolinePrice*, which is specific to the month in which the vehicle was purchased and to the DMA of the buyer. We use the same demographic and purchase timing covariates and the same region-specific year and region-specific month-of-year fixed effects that we used to estimate the effect of gasoline prices on new car prices in Equation 2, although in estimating Equation 5 we cannot use the "car type" fixed effects that we used to estimate Equation 2 because "car type" would perfectly predict the fuel economy quartile of the transaction. We will estimate Equation 5 four times, once for each fuel economy quartile.

In order to estimate the effect of gasoline prices on unit sales, we use two different measures of unit sales. The first measure we use aggregates our individual transaction data into unit sales by dealer, for each month, by MPG quartile.[26] Using this measure, we estimate:

$$Q_{dkrt} = \gamma_0 + \boldsymbol{\gamma_1}(\text{GasolinePrice}_{dt} \cdot \text{MPG Quartile}_k) + \boldsymbol{\gamma_2}\text{MPG Quartile}_k + \delta_d + \tau_{rt} + \mu_{rt} + \epsilon_{dkrt}. \quad (6)$$

Q_{dkrt} is the unit sales at dealer d located in region r for vehicles in MPG quartile k that occur in month t. The variable of primary interest is the *GasolinePrice* in month t in the DMA in which dealer d is located. The coefficients of primary interest are $\boldsymbol{\gamma_1}$. These coefficients estimate the average effect of gasoline prices on new car sales within a fuel economy quartile. We include fixed effects for each of the MPG quartiles and for individual dealers (δ_d). Finally, as in Equation 5, we include year, τ_{rt}, and month-of-year, μ_{rt}, fixed effects that are are allowed to vary by the geographic region of the dealer.

While this measure enables us to look at effects on unit sales (instead of market share) while still controlling for many local characteristics (via dealer fixed effects), the estimated coefficients will represent the effects on sales at an average dealer. In our final specification, we measure sales at

[24]Our results do not depend on the linear probability specification; we obtain nearly identical results with a multinomial logit model (see section 7.6).

[25]In previous versions we have used classes based on segments (e.g., compact, SUV, midsize). These results are available from the authors.

[26]We aggregate from our full data set, not the 10% random sample that we use elsewhere in the paper.

the national level using information from Ward's Auto Infobank.[27] Using these data, we estimate:

$$Q_{kt} = \gamma_0 + \boldsymbol{\gamma_1}(\text{GasolinePrice}_t \cdot \text{MPG Quartile}_k) + \boldsymbol{\gamma_2}\text{MPG Quartile}_k + \tau_t + \mu_t + \epsilon_{kt}. \quad (7)$$

Q_{kt} is the national unit sales for vehicles in MPG quartile k that occur in month t.[28] The variable of primary interest is again *GasolinePrice*, which is now measured as the national average in month t. The coefficients of interest are the four coefficients in the vector $\boldsymbol{\gamma_1}$ which represent the effects of gasoline prices on the sales of cars in each of the four MPG quartiles. We include fixed effects for each of the MPG quartiles, and for year, τ_t, and month-of-year, μ_t.[29]

4.5 New car market share results

We first consider the effect of gasoline prices on the market shares of new cars in different quartiles of fuel economy. Quartiles are re-defined each year based on the distribution of all models *offered* (as opposed to the distributions of vehicles sold) in that year.

In order to estimate Equation 5, we define four different dependent variables. The dependent variable in the first estimation is 1 if the purchased car is in fuel economy quartile 1, and 0 otherwise. The dependent variable in the second estimation is 1 if the purchased car is in fuel economy quartile 2, and 0 otherwise, and so on. To account for correlation in the errors due to either supply or demand factors, we cluster the standard errors at the DMA level.

The full estimation results are reported in Table A-4. The estimated gasoline price coefficients ($\boldsymbol{\gamma_1}$) for each specification are presented in Table 3. We also report the standard errors of the estimates, and the average market share of each MPG quartile in the sample period. (Since the quartiles are based on the distribution of available models, market shares need not be 25% for each quartile.) Combining information in the first and third column, we report in the last column the percentage change in market share that the estimated coefficient implies would result from a $1 increase in gasoline prices.

These results suggest that a $1 increase in gasoline price *decreases* the market share of cars in the lowest fuel economy quartile by 5.7 percentage points, or 27.1%. Conversely, we find that a $1

[27] Our transaction data are from a representative sample of dealers, according to our data source. So one approach might be simply to use our data and multiply by the inverse of the sample percentage to get a national figure. Unfortunately, the sample percentage changes slightly over time, and we don't know the year-to-year scaling factor.

[28] Ward's reports sales data for some cars by a more aggregate model designation than the EPA uses to report MPGs. We use the sales fractions in our transaction data to allocate models to which this issue applies in the Ward's data into MPG quartiles.

[29] In results available from the authors, we use a third unit sales measure. That third measure uses the information in our transaction data about the regional distribution of sales within an MPG quartile to divide the Ward's national sales into regional sales. Specifically, for each month in the sample, we calculate from the transaction data the fraction of sales in each MPG quartile that occurred in each region. We then designate that fraction of the Ward's sales in the corresponding MPG quartile to have occurred in the corresponding region.

Table 3: Gasoline price coefficients from new car market share specification

Fuel Economy	Coefficient	SE	Mean market share	% Change in share
MPG Quartile 1 (lowest fuel economy)	-0.057**	(0.0048)	21.06%	-27.1%
MPG Quartile 2	-0.014**	(0.004)	20.95%	-6.7%
MPG Quartile 3	0.0002	(0.0027)	24.28%	0.1%
MPG Quartile 4 (highest fuel economy)	0.071**	(0.0058)	33.72%	21.1%

increase in gasoline price *increases* the market share of cars in the highest fuel economy quartile by 7.1 percentage points, or 21.1%. This provides evidence that higher gasoline prices are associated with the purchase of cars with higher fuel economy.[30] Notice that these estimates do not simply reflect an overall trend of increasing gasoline prices and increasing fuel economy; since we control for region-specific year fixed effects, all estimates rely on within-year, within-region variation in gasoline prices and car purchases.[31]

4.6 New car sales results

While the market share results allow us to investigate the effect of gasoline prices on automobile purchase choices while controlling for transaction- and buyer-specific characteristics, they do not allow us to draw inferences directly about changes in unit sales. Changes in gasoline prices may be correlated, for macroeconomic reasons, with changes in the total number of vehicles sold. A higher market share of a smaller market could correspond to a unit decrease in sales, just as a smaller market share of a bigger market could correspond to a unit increase in sales. In this subsection, we report the results of our two unit sales specifications, Equation 6 and Equation 7.

The coefficient estimates for these two specifications are reported in Tables 4 and 5. The tables report the estimated gasoline price coefficients for each of the four MPG quartiles, the average unit sales, and the percentage change relative to the average implied by the coefficients for a \$1 increase in the price of gasoline. On average, dealers sell 11.2 cars per month in the lowest fuel economy quartile of available cars; a \$1 increase in gasoline prices is estimated to reduce that number by 3.1 cars, or 27.7%. On average, dealers sell 17.8 cars per month in the highest fuel economy quartile of cars; a \$1 increase in gasoline prices increases that number by 2.1 cars, or 11.8%. Adding up the predicted effects across quartiles shows that an increase in gasoline prices is predicted to reduce the total sales of new cars. Consistent with this, the percentage changes in unit sales are more negative quartile-by-quartile than the percentage changes in market share reported in the previous subsection.[32]

[30] While we do not restrict the γs to sum to zero, the sum of the coefficients (at seven decimal points) equals 0.

[31] Nor are the results due to seasonal correlations between gasoline prices and the types of cars purchased at different times of year, since the regressions control for region-specific month-of-year fixed effects.

[32] This is consistent with Knittel and Sandler (2010) which finds that increases in gas prices reduces the scrappage rates of used vehicles, in aggregate.

Table 4: Gasoline price coefficients from dealer-level unit sales specification

Fuel Economy	Coefficient	SE	Average cars sold per month in dealer	% Change in sales
MPG Quartile 1 (lowest fuel economy)	-3.1**	(.091)	11.2	-27.7%
MPG Quartile 2	-0.83**	(.087)	11.1	-7.5%
MPG Quartile 3	-0.71**	(.088)	13.0	-5.5%
MPG Quartile 4 (highest fuel economy)	2.1**	(0.11)	17.8	11.8%

According to the estimates using the Ward's national sales data, reported in the next table, when gasoline prices increase by $1, there are 79,169 fewer cars per month sold in the lowest fuel economy quartile of cars. This is a 27.2% decrease relative to the 291,533 monthly average in this quartile. In the highest fuel economy quartile, a $1 increase in gasoline prices is associated with an increase in monthly sales of 40,116 cars, a 10.8% increase on the average monthly sales in this quartile of 372,998.

Table 5: Gasoline price coefficients from national unit sales specification

Fuel Economy	Coefficient	SE	Average cars sold per month nationally	% Change in sales
MPG Quartile 1(lowest fuel economy)	-79,169**	(9,421)	291,533	-27.2%
MPG Quartile 2	-14,761	(9,994)	262,453	-5.6%
MPG Quartile 3	-30,029**	(9,609)	329,466	-9.1%
MPG Quartile 4 (highest fuel economy)	40,116**	(11,800)	372,998	10.8%

Overall, the results we obtain using unit sales tell a very consistent story whether they are measured at the dealer or national level. They are also broadly consistent with the market share results estimated in the previous subsection, with the primary difference that the unit sales results reveal a reduction in total car purchases when gasoline prices increase that is masked in the market share results.

4.7 Used car transaction share results (an aside)

While we can easily estimate Equation 5 using our data on used car transactions, the estimates do not have the same interpretation as the estimates for new cars. Changes in the market share of new cars measure how the incremental additions to the U.S. vehicle fleet change when gasoline prices change. The analogous estimates arising from the used car data would not measure changes in market share in this sense, but instead changes in "transaction share;" namely how gasoline price affects the share of used car transactions that are for cars in different quartiles. For completeness, we present these results briefly.

We estimate Equation 5 using data from used car transactions at the same dealerships at which we observe new car transactions. The full results of transaction share effects of gasoline prices by

MPG quartiles are reported in Table A-5. The gasoline price coefficients are as follows:

Table 6: Gasoline price coefficients from used car transaction share specification

Fuel Economy	Coefficient	SE	Mean share	% Change in share
MPG Quartile 1 (lowest fuel economy)	0.00018	(0.0069)	24.19%	0.07%
MPG Quartile 2	-0.007	(0.006)	20.89%	-0.04%
MPG Quartile 3	0.017	(0.011)	27.32%	6.2%
MPG Quartile 4 (highest fuel economy)	-0.009	(0.0074)	27.61%	-0.03%

The results are both smaller in magnitude and weaker in statistical significance than the analogous results for new cars.

Summary of results

Overall, we see a modest effect of gasoline prices on new car transactions prices. The predicted effect of a $1 gasoline price increase is to increase the price difference between the highest and lowest fuel economy quartiles of new cars by $354. The estimated effects are much larger for used cars; in this market, the predicted effect is to increase the price difference between the highest and lowest fuel economy quartiles by $1,945.

We find both statistically and economically significant effects of gasoline prices on new car sales, measured either as market shares or by unit sales. This is particularly true for the highest fuel economy and lowest fuel economy quartiles, where market share shifts by more than 20% in response to a $1 increase in gasoline prices, and where unit sales decrease by more than 25% for the lowest fuel economy quartile and rise by more than 10% for the highest fuel economy quartile.

5 Consumer valuation of future fuel costs

In this section, we draw upon the estimates in the previous section to investigate whether consumers exhibit "myopia" about future fuel costs of different cars when they are considering the up-front purchase decision. We will begin by describing our empirical approach.

5.1 Empirical approach

The basic starting point for the consumer myopia literature is a simple idea: if the expected future usage cost of a durable good increases, all else equal, then the price of that durable good should fall by the same amount. In other words, consumers' total willingness-to-pay for the good should be unchanged by a change in one of the cost components, all else equal. This means that if the usage cost component of the total cost rises, the up-front cost must fall if consumers are to keep purchasing the good. A direct approach to testing whether consumers "correctly" value future fuel costs would be to estimate a demand relationship in which expected future fuel costs were included as a covariate, and test whether the relevant coefficient has the value that would be implied by consumers correctly valuing fuel costs.

In the automotive setting, there are two difficulties to actually estimating this relationship. One is that, in the cross-section, differences between cars in fuel costs are often related to differences between those cars in other attributes that are valued by consumers as goods; for example, size, weight, power, or other, unobservable attributes. This can make the empirical cross-sectional relationship between price and fuel cost positive. Of course, adequate controls for characteristics, or detailed car fixed effects, could remedy this.[33]

A second problem is that if intertemporal variation in gasoline prices is used to identify the relationship between a car's price and its future fuel cost, the "all else equal" condition is violated: a rise in the price of gasoline which increases the cost of operating one car will increase the cost of operating *all* gasoline-powered cars. This means that if consumers are sufficiently unwilling to substitute away from cars as a whole, a rise in the price of gasoline might well *increase* the price of cars with relatively high fuel economy even if their operating costs have actually gone up, because the operating cost would have decreased *relative* to that of a low fuel economy car.

To see how this latter point affects the estimation of the relationship between future fuel costs and car prices, consider a market with two vehicles, 1 and 2. Suppose that the price of vehicle i is given by p_i and that the present discounted value of the expected future gasoline cost for operating vehicle i over its lifetime is given by G_i. For simplicity, suppose that demand is linear, implying the demand for vehicle 1 can be written as:

$$q_1 = \alpha_1 + \beta_{11}(p_1 + G_1) + \beta_{12}(p_2 + G_2) \tag{8}$$

Solving this for price implies the following relationship:

$$p_1 = -\gamma G_1 + \frac{1}{\beta_{11}} q_1 - \frac{\alpha_1}{\beta_{11}} - \frac{\beta_{12}}{\beta_{11}}(p_2 + G_2) \tag{9}$$

where $\gamma = -1$ is implied by consumers who correctly value future fuel costs. One could test whether consumers really do behave this way by estimating γ as a free parameter.

There are three difficulties in estimating this relationship in practice. First, a general model would have to specify the price of vehicle i as a function of the fuel cost of vehicle i and of the fuel costs of all other vehicles separately. Given the large number of vehicles offered in the U.S. market,

[33] A recent example of a paper that takes this approach is Espey and Nair (2005), who estimate a hedonic regression of list prices on a variety of attributes for a cross-sectional sample of 2001 model year cars. They conclude that consumers use fairly low discount rates when valuing future fuel cost savings.

this would be difficult to implement.[34] A second difficulty is that there may be endogeneity between q_i and p_i, arising from a supply relationship between the two variables. A third difficulty is that the econometrician must have a good model of how the marginal consumer constructs the present discounted value of the expected future gasoline cost. The inputs necessary for constructing this variable are expectations of future gasoline prices, expected future driving behavior (vehicle miles travelled), the discount rate, and the miles-per-gallon of the car. Of these, only the last is likely to be observable as data. If the present discounted value of the expected future gasoline cost is mismeasured, then attenuation bias is likely to exist, biasing the researcher toward concluding that consumers are myopic.

In this paper, we will take an alternative approach. Our approach is to combine our reduced-form estimates of price and quantity effects with estimates of the elasticity of demand for new cars, and estimates of future gasoline prices, vehicle miles travelled, and discount rates in order to address the question of whether consumers are myopic with respect to future fuel costs. While our approach will lack the elegance of addressing the question in a single estimated parameter, it will be more amenable to examining the effect of a variety of assumptions about vehicle miles travelled, future gasoline prices, and discount rates. We will present a range of estimates; it will be fairly straightforward for readers to substitute their own assumptions as well.

5.2 Consumer myopia results

In this subsection we address the question of whether consumers are myopic about future gasoline prices when they make car purchase decisions. Analyzing this means, in simple terms, comparing the effects of gasoline price changes on buyers' willingness-to-pay for cars of different fuel economies to the changes in the discounted value of future gasoline costs that is implied by the gasoline price change and the fuel economy of the car. In practice, there are a few wrinkles.

First, to calculate the discounted value of expected future gasoline costs we need to know how many miles car owners drive in a given year, conditional on the car surviving through that year, and also annual survival rates. We calculate miles driven, conditional on survival, three ways. We use NHTSA-assumed values for annual miles driven, separately for cars and light duty trucks, by vintage. These data are used in a number of modeling efforts for both the NHTSA and DOT (Lu (2006)). Our other two measures come from within our data: we compute the average annual miles driven, by vintage, separately for cars and trucks, for vehicles in our used car transaction data and

[34] An alternative approach, used by Allcott and Wozny (2011), is to specify a nested logit demand system and then to solve for equilibrium prices. The benefit of this approach is that in the logit model the usage cost of all other vehicles drops out of the estimating equation once the market share of each car is divided by the share of the outside good. The cost is that it imposes a specific functional form assumption on the data. If the model is not a good match for the data, the estimates could lead to erroneous inferences.

for all trade-ins we observe being used to purchase either new or used cars in our transaction data. If the typical new or used car purchased at our dealers is replacing the trade-in, one could argue that the calculations based on the miles driven of trade-ins most accurately reflect the driving patterns of those consumers in our data. We also use vehicle survival rates from NHTSA to calculate the expected miles driven for each year of the vehicle's life. Because the median used car is four years old at the time of purchase, we calculate miles driven beginning at the fourth year of life for used cars.

Second, we model consumers' expectations of future gasoline prices as following a random walk for real gasoline prices. This has the convenient implication that the current gasoline price is the expected future real gasoline price. (Anderson, Kellogg, and Sallee (2011), discussed in more detail in Section 7.2, show empirical evidence that this is indeed the gasoline price expectation that consumers have on average.) One alternative is to assume that consumers are more sophisticated and use information on crude oil futures markets to make projections into the future.[35] It turns out that during our sample period, the random walk is the more conservative assumption. This is because for the vast majority of time during our sample, the crude market was in backwardation; that is, the market expected crude prices to fall (See Figure A-1 for a plot of both the spot crude price and the stream of expected prices in subsequent years for May of each year—the "forward curve.") This means that if consumers actually use crude futures prices to form expectations, and we assume instead that they use a random walk, then for any observed set of changes in willingness-to-pay for cars of different fuel economies, consumers would be more patient than our estimates would show.[36] In other words, our approach biases us to finding myopia.

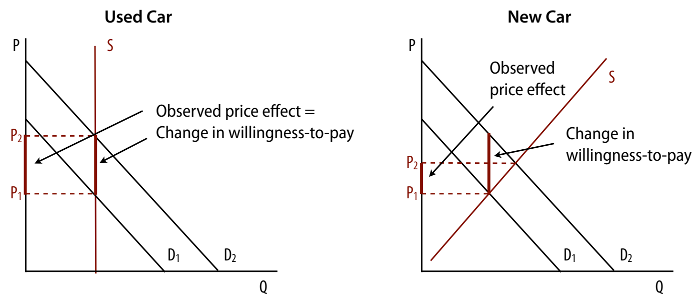
Third, we need to know what discount rate customers use to discount future gasoline costs. We reserve this to be our free parameter. In other words, we use estimates and make assumptions about the various other components of the calculation, and see what they imply for the discount rate.

Fourth, in order to address the question of myopia, we need to observe the effects of gasoline prices on consumers' *willingness-to-pay* for cars of different fuel economy; what we have estimated so far is the effect of gasoline prices on *equilibrium transaction prices*. In order to translate a change in equilibrium price to a change in willingness-to-pay, we need to consider supply and demand in the new and used car markets. In the used car market, one might argue that a fixed supply curve is a reasonable assumption for used car supply. (See the discussion in Section 6 for the argument.) This means that the equilibrium price effect will be equal to the change in willingness-to-pay. (Figure 3

[35]See section 7.2 for the results of such an approach.

[36]A third justification for using current gasoline prices is that consumers may not be sophisticated in forming expectations, and may base their decisions on the most salient gasoline price they see—the one currently posted at gas stations nearby.

Figure 3: Effects of gasoline price change on hypothetical used and new cars



shows a representation of this for a hypothetical used car model.) However, in the new car market, one might well think that the supply relationship is more flexible and that auto manufacturers and car dealers likely have some scope to respond to changes in demand by altering prices, quantities, or both. (Again, see the discussion in Section 6.) This means that the equilibrium price effect will be less than the change in the willingness-to-pay, and that the difference between the two will be greater the more inelastic the demand curve is. (Figure 3 shows a representation of this for a hypothetical new car model.)

Since we estimate the equilibrium effects on prices and quantities, we could recover the implied effects of gasoline price changes on willingness-to-pay if we had an estimate of the elasticity of demand, as well as an assumed functional form for demand. While estimating an elasticity of demand is beyond the scope of this paper, there are a number of existing papers that have done just this. Goldberg (1995) estimates residual demand elasticities of demand for specific vehicles that are in the neighborhood of -2 to -4, while Berry, Levinsohn, and Pakes (1995) estimate elasticities in the -3 to -6 range.[37] We note that these estimates should be strong upper bounds (in absolute value) to the relevant demand elasticity for our purposes. The estimates in Goldberg (1995) and Berry, Levinsohn, and Pakes (1995) are residual demand elasticity estimates for a *specific* vehicle, which are likely to be higher than the demand elasticity for a vehicle in a particular fuel economy quartile, which is the relevant elasticity for us. Finally, we assume that demand has a constant elasticity functional form.[38]

In the table below, we present the results of our investigation into the question of whether consumers are myopic. The entries in the last three columns are the implied discount rates necessary

[37] Goldberg (1995) reports average elasticites by vehicle segment and origin. The average elasticity across segments is -3.4, while the median is -3.5. Berry, Levinsohn, and Pakes (1995) report elasticity estimates for 13 specific vehicles. Assuming these are representative of the sample, the average elasticity is -5, while the median is -4.8.

[38] The assumption of a constant elasticity demand function has the benefit that, in order to make our calculations, it requires only percentage changes in equilibrium quantities. The calculations assuming a linear demand model where the slope and intercept are chosen such that the elasticity equals that of the constant elasticity demand curve at the average price and quantity are very similar to those reported here.

to equate the relative price differences between vehicles of different fuel economies to the relative differences in discounted expected future fuel costs between those vehicles. The relative price differences we use are the estimates from Table 1 for new cars and from Table 2 for used cars. Because the expectation of future gasoline prices we have used is an expectation about real, not nominal, gasoline prices, the implied discount rates we calculate do not contain inflation expectations. Note that the table presents a range of possible estimates of the implied discount rate that hold for a particular set of assumptions.[39] Changing those assumptions would, of course, change the implied discount rates obtained.[40]

The top panel of Table 7 reports the implied discount rates when comparing the estimated price effects for the lowest fuel economy quartile of cars relative to the highest fuel economy quartile. The middle panel reports for the lowest fuel economy quartile relative to the quartile with second highest fuel economy; the bottom panel for the quartile with second lowest fuel economy relative to the highest fuel economy quartile. The top row of each panel reports the implied discount rates based on the relative price effects estimated for used cars. The next four rows report the implied discount rates based on the relative price effects estimated for new cars, adjusted to implied willingness-to-pay effects using elasticities of demand ranging from -2 to -5. Finally, the three columns use estimates of vehicle miles travelled from NHTSA, from the used car transactions in our data, and from the trade-ins in our data, respectively.

Overall, the implied discount rates range from moderate to quite small. In most cases, the estimates are in the single digits, with some combinations of assumptions actually implying negative discount rates. The more elastic new vehicle demand is assumed to be, the smaller the implied change in willingness-to-pay is for a given relative price difference, and the higher is the implied discount rate necessary to rationalize the willingness-to-pay change with a given change in expected future gasoline costs. Since the largest elasticity for new vehicles we use in Table 7 was calculated for individual vehicles rather than for quartiles, whose demand is presumably less elastic, the estimates that use the lower values for elasticities may be the most relevant. The implied discount rates arising from used car prices are generally higher than those implied by new car prices, although the ranges overlap. Most of the estimates of implied discount rates are near or below typical rates for car loans. In our sample, the 10th to 90th percentile range of APRs for consumers financing their car purchase through the dealer is [1.9%, 11.6%] for new car buyers and [5.5%, 19.7%] for

[39] The spreadsheet that makes this calculations—and could be used to show the influence of different assumptions from those presented here—is available from the authors.

[40] One plausible effect of gasoline prices that is not included in the assumptions underlying Table 7 is that vehicle miles travelled fall when gasoline prices increase. If this is the case, then the expected future fuel costs of cars of different fuel economies will be more similar than what we have assumed for the table, meaning that implied discount rates will have to be smaller in order to reconcile the estimated change in willingness-to-pay with the change in expected future fuel costs.

Table 7: New and Used Cars: Implied Discount Rates

	Market	Assumed Demand Elasticity	NHTSA VMT, NHTSA Survival Rates	VMT from Used Car Transactions, NHTSA Survival Rates	VMT from Tradeins, NHTSA Survival Rates
Q1 vs. Q4	Used	NA	11.6%	4.3%	5.9%
	New	-2	-3.5%	-6.6%	-6.1%
	New	-3	1.6%	-2.6%	-1.9%
	New	-4	6.3%	0.1%	2.0%
	New	-5	10.7%	4.1%	5.6%
Q1 vs. Q3	Used	NA	7.0%	0.4%	2.0%
	New	-2	-3.5%	-6.6%	-6.1%
	New	-3	1.7%	-2.6%	-1.8%
	New	-4	6.4%	0.1%	2.0%
	New	-5	10.8%	4.2%	5.5%
Q2 vs. Q4	Used	NA	20.0%	11.2%	13.0%
	New	-2	1.8%	-2.5%	-1.7%
	New	-3	8.9%	2.8%	4.1%
	New	-4	15.5%	7.7%	9.4%
	New	-5	22.0%	12.2%	14.4%

used car buyers. These APRs are nominal interest rates. During our sample period, inflation rates were between 1.1 and 5%. We calculate "real APRs" by subtracting from each APR observation the inflation rate in the same month. The 10th to 90th percentile range for "real APRs" is [-1.2%, 8.8%] for new car purchases and [2.5%,16.8%] for used cars.[41] While some of the implied discount rates fall outside this range, the evidence in Table 7 suggests that the discount rates people use to evaluate future fuel costs are generally comparable to interest rates they pay when they buy a car.

We conclude that there is little evidence that consumers dramatically undervalue changes in expected future fuel costs, and that the evidence from new and from used cars yield similar messages. Our findings on this are similar to Allcott and Wozny (2011) who calculate that their results correspond to a 16% implied discount rate, and to Sallee, West, and Fan (2009) who find somewhat less undervaluation of future fuel costs than do Allcott and Wozny (2011). It bolsters our confidence in the results of this entire set of papers that different configurations of identifying assumptions yield similar results. In our view, this lessens the worry readers should have that the results in any of these papers arise directly from a particular set of assumptions.

6 Market structure and the effect of policy intervention

Two of the policy interventions that have been advocated by economists in the public discussion of climate change policy are an increased gasoline tax and a carbon tax. Both would reduce the incentive for drivers to use gasoline. Drivers could respond to this changed incentive by altering

[41] The new car APRs are negative when manufacturers subsidize interest rates to fall below market rates.

their driving habits, changing their vehicles, or both. In this section we argue that in order to predict the effect of such a policy intervention on vehicle markets, one has to consider the market structure of the vehicle market itself.[42]

We begin by noting that the new and used car markets which we observe are similar in many ways. All the transactions in our data occur at new car dealerships; at many of these dealerships, the same salesperson sells both new and used cars. The used cars sold at new car dealerships are also a positive selection of used cars; the average price of a used car in our sample is \$15,637 compared to \$25,515 for a new car. The consumers in our sample who buy used cars are also not dissimilar to those who buy new cars. For example, on average, a used car buyer comes from a Census block group with a median household income of \$50,684 vs. \$58,130 for new car buyers.

Where the two markets differ is in the *supply* of new and used cars. New cars are supplied by the combined activities of auto manufacturers and dealers, while the supply of used cars arises ultimately from the cumulated new car purchases of past years. For new cars, auto manufacturers decide on the prices and quantities of each model they wish to sell. Prices can be adjusted quickly by using promotions (Busse, Silva-Risso, and Zettelmeyer 2006). Production quantities can be adjusted by adding or reducing shifts on assembly lines (Bresnahan and Ramey 1994), or for some modern manufacturing plants by adjusting which kinds of vehicles are produced on a given line.[43] Car dealers can easily adjust the prices they negotiate with individual customers, and can adjust quantities by changing inventory holdings and orders to manufacturers. Manufacturers are likely to have market power in the supply of a particular model because of the differentiation of individual car models, and dealers because of local market power. So both have some discretion, when faced with a change in demand, to absorb the change in the model's price, in its quantity, or in a combination of the two. Profit maximization will determine what the optimal response is depending on the shape of each model's demand and marginal cost curves.

The stock of used cars is predetermined by the cumulation of past new car purchases, and is likely to respond very little to gasoline prices.[44] Many cars sold on the used market are fleet turnovers and lease returns whose entry into the used car market will not be determined primarily by gasoline prices. If consumers are also driven to replace their existing cars by factors unrelated to gasoline prices, the supply of a particular used car model at any point in time could be thought

[42] Similar points are made by Busse and Keohane (2007) about sulfur dioxide regulation and low-sulfur coal markets and by Mansur (2007) and Fowlie (2010) about nitrogen oxide regulation and electricity markets.

[43] For example, Honda can build the compact Civic on the same assembly line that builds the Ridgeline pickup and the Acura MDX SUV ("Adaptability helps Honda weather industry changes," Automotive News, June 8, 2009). In 2008, the last year in our sample, the Civic was in highest fuel-economy quartile of cars while the Acura MDX was in the lowest fuel-economy quartile.

[44] Davis and Kahn (2010) suggest that some low-MPG vehicles may be more likely to be traded to Mexico when the U.S. price of gasoline deviates greatly from the prices set by PEMEX, the national petroleum company.

of as essentially fixed. If this is the case, then the effect of a change in demand for that model ought to show up almost entirely in the equilibrium prices of used cars of different types, and could have very little effect on equilibrium unit sales or transactions shares.[45]

Used car auctions also help facilitate rapid adjustment of prices. A large fraction of wholesale transactions for used cars go through independent auctions, unaffiliated with car manufacturers. Auction sites are ubiquitously available throughout the country, each transacting 1,000-3,000 cars in a typical week. The auction price can adjust to changes in equilibrium market conditions quite quickly. Since the auction price represents the outside option for any car on a dealer's lot, the existence of auctions will lead prices of used cars sold at car dealerships to adjust fairly quickly to market-clearing equilibrium prices that reflect changes in gasoline prices.

The results that we have estimated in the paper so far are consistent with these differences between new and used car supply. We find that equilibrium prices for used cars change in response to changes in gasoline prices by roughly an order of magnitude more than do prices for new cars. In the new car market, however, we estimate substantial effects of gasoline prices on the market shares and sales of new cars. This suggests that the new car supply chain—manufacturers and dealers combined—is choosing to respond to changes in demand by changing prices relatively little, and absorbing the effect of the demand change in quantities—inventories or production levels—instead.

In this section, we present two pieces of supplementary evidence. First, we show that changes in inventory are consistent with the changes in sales we have presented already. Second, we show that the large effects we estimate for used car transaction prices are reflected also in dealers' internal valuations of used cars.

6.1 Inventories

In our data, we observe a variable called "days to turn" which counts the number of days that a specific vehicle was on a dealer's lot before it sold. Higher average days to turn for vehicles in a particular class of cars indicates higher dealer inventories for that class of car.

[45] One might argue instead that a car owner's decision to sell a used car *should* be influenced by gasoline prices; for example, a commuter with a large SUV might be encouraged by high gasoline prices to sell or trade-in that car in order to replace it with a higher-MPG car. We would argue that even if this is true, the effect of gasoline price changes is likely to show up primarily in used car prices. To see this, consider a potential seller and a potential buyer of a particular low-MPG used car. If the gasoline price increases by some amount, then the *per-mile* cost of driving that particular car increases by the same amount for both drivers. If the two drivers have approximately the same driving habits, then one might expect the effect of the gasoline price increase on the buyer and the seller to be symmetric: for both the current owner and the potential buyer, the increased cost of usage for the current owner of that car will exactly equal the increased cost of usage for the potential buyer if she buys the car. Taking this logic one step further, if most drivers have similar driving habits (or if a large enough number of marginal buyers and sellers have similar driving habits), then the demand curve for a used car should shift inward by roughly the same amount that the supply curve for that car shifts outward (at least in the area of the demand and supply curves where equilibrium occurs).If this were the case, then the prices of a particular used car should adjust to reflect the value of the fuel expenditure disadvantage (or advantage) that car has, given the new gasoline prices.

In order to investigate inventory effects, we estimate the effect of gasoline prices on days to turn by MPG quartiles. (The specification and results are reported in Table A-6.) We find that gasoline prices have a larger effect on days to turn for new than for used cars. For new cars, the estimated coefficients imply that a $1 increase in gasoline price is associated with a 12-day increase in days to turn for cars in the lowest fuel economy quartile, a 17.7% increase from the sample mean of 67.7 days. The same gasoline price increase reduces by 5.5 days the time that a car in the highest fuel economy quartile remains on the lot, an 11.5% decrease relative to an average of 48.9 days. In contrast, for used cars, higher gasoline prices have a much smaller effect on days to turn. The estimated effect for the lowest fuel economy quartile is a (statistically insignificant) 0.95-day (or 2.0%) increase and for the highest fuel economy quartile is a 1.9-day (or 4.3%) decrease.

6.2 Actual cash value of trade-ins

In our data, we also observe what dealers book as the "actual cash value" of trade-ins they receive. While a dealer might wish to manipulate the *price* paid to the customer for his or her trade-in, the "actual cash value" is the dealer's internal assessment of the value of the vehicle. In this number, the dealer is trying to approximate the price for which it could have purchased—or could sell—the car at auction. We are interested in how the actual cash value of cars of different fuel economies varies with gasoline prices.

In regressions described and reported in Table A-7, we estimate the effect of gasoline prices on the actual cash value of trade-ins of different fuel economies and find results similar to the those obtained for the gasoline price effect on used car prices. The results in Table 2 imply that when gasoline prices increase by $1, the price of a used car in the highest fuel economy quartile rises by $1,945 relative to that of a used car in the lowest fuel economy quartile. The results in Table A-7 imply that when gasoline prices rise by $1, the actual cash value of a trade-in car in the highest quartile of fuel economy rises by $1,556 relative to that of a trade-in car in the lowest fuel economy for trade-ins used to by new cars, and by $775 for trade-ins used to buy used cars. This result is consistent with our argument that most of the adjustment to changes in demand in the used car market occur in prices, and that prices are aided in their rapid adjustment by a well-functioning wholesale market.[46]

[46]Trade-in cars are not entirely comparable to the used cars in our sample. Used cars sold in our sample sell for a median price of $14,461, compared to $6,794 for new car trade-ins and $3,000 for used car trade-ins. The compression in the range of actual cash values compared to used car prices may explain why the gasoline price effects on actual cash values are smaller than the gasoline price effects on used car prices.

Summary

One of the chief arguments for an increased gasoline tax or a carbon tax in car markets is that it would cause buyers to change the type of vehicle they buy, and thereby future gasoline consumption. The results we have estimated for the effect of gasoline prices in new car markets suggests that this would indeed be the effect of such interventions. This section has pointed out, however, that it is important to be mindful of the market structure of the target market when such an intervention is contemplated. If the new car market were structured like the used car market (very inflexible supply and mechanisms to facilitate rapid adjustment to competitive market prices), then the effect on vehicle market shares or volumes likely would be much smaller.

7 Robustness

In this section we explore the robustness of our results. First, we analyze whether our results are robust to changing the component of variation in the data that is used to identify the effect of gasoline prices. Second, we investigate the effect of using an estimate of future gasoline prices (based on oil price futures) instead of current gasoline prices as our explanatory variable of interest. Third, we allow the response to gasoline price to differ by the level and prior direction of gasoline prices to see whether we are ignoring important response heterogeneity in our estimates. Fourth, we analyze the robustness of our findings to the aggregation of gasoline prices. Fifth, we analyze whether we should treat gasoline prices as being endogenous. Sixth, we examine whether our results depend on our use of a linear probability model to estimate market share changes in response to gasoline prices.

7.1 Source of variation

We now re-estimate the original specifications in this paper with a series of different fixed effect combinations. So far, all specifications have controlled for region-specific year and region-specific month-of-year fixed effects. This means that the estimated gasoline price effects have been identified by within-year, region-specific variation in price, market share, or sales which deviates from region-specific seasonal effects.

In order to investigate the robustness of theses estimates, we estimate eight additional specifications with different combinations of fixed effects. Five specifications are more parsimonious than our base specifications reported in Tables 1, 2, and 3, meaning that less of the variation in the left-hand-side variable is absorbed by fixed effects, and three specifications are richer, meaning that more of the variation is absorbed into fixed effects. Table 8 reports the results for new car prices, Table 9 for used car prices, and Table 10 for new car market shares. The most parsimo-

Table 8: Effect of time and seasonal fixed effects in new car price specification[†]

	Region FE	Time FE	Seasonal FE	MPG Quartile 1	MPG Quartile 2	MPG Quartile 3	MPG Quartile 4	Price change Quar 1 to 4
1	Region	–	–	-520** (82)	-373** (45)	-286** (31)	-165** (42)	$355
2	Region	–	Month-of-year	-251** (73)	-98* (40)	-19 (33)	87+ (49)	$338
3	Region	Year	Month-of-year	-245** (73)	-102** (37)	-17 (31)	82+ (49)	$327
4	–	–	Month-of-year × Region	-255** (73)	-104* (40)	-26 (34)	84+ (50)	$339
5	–	Year	Month-of-year × Region	-250** (73)	-108** (38)	-25 (32)	78 (50)	$328
6 (Base)	–	Year × Region	Month-of-year × Region	-250** (72)	-96** (37)	-11 (26)	104* (47)	$354
7	–	Year × Region Year × Trend	Month-of-year × Region	-205** (68)	-62+ (35)	18 (29)	127* (51)	$332
8	–	Quarter × Region	Month-of-year × Region	-161* (68)	-16 (41)	66+ (35)	171** (58)	$332
9	–	Month × Region		-313* (157)	-177 (152)	-90 (155)	14 (173)	$327

[*] significant at 5%; ** significant at 1%; + significant at 10% level. SEs (robust and clustered at the DMA level) in parentheses.

nious specification includes only region fixed effects (no year or month-of-year fixed effects) and the richest specification uses month (not month-of-year) times region or PADD fixed effects. For ease of comparison, in all the tables, row 6 reports the results of our base specification.

In Tables 8 and Table 9, the most direct way to compare the price estimates across rows is to compare the implied change in the price of a car in quartile 1 relative to a car in quartile 4. This number is reported in the last column of both tables. For new cars (Table 8), the implied change in relative prices ranges from $327 to $355. This includes the results in row 9, which use monthly fixed effects. For used cars (Table 9), it ranges from $1,917 to $2,563, although the first seven rows vary only from $1,917 to $2,196. The fact that our estimates fall within a $28 range for new cars and a $279 range for most of the used car results seem to us to be quite stable results, especially considering the differences in the components of variation used to identify the effects in different rows. (Increasing the frequency of the time fixed effect, in rows 8 and 9, has bigger effect on the used car results than on the new car results. Using these estimates would reduce the implied discount rates relative to what is reported in Table 7.)

Table 10 repeats the exercise for the market share specification. We find that the estimated effect of a $1 increase in gasoline price on the market share of new cars in the lowest fuel economy quartile ranges from -4.8 percentage points to -7 percentage points. The effect on the market share of the highest fuel economy quartile ranges from 5.8 to 8.7 percentage points. The effect in quartile 2 ranges from 2.9 percentage points to statistically zero, and the effects for quartile 3 are almost all statistically zero. The results seem to us to be again quite stable. The one exception to this

Table 9: Effect of time and seasonal fixed effects in used car price specification†

	Region FE	Time FE	Seasonal FE	MPG Quartile 1	MPG Quartile 2	MPG Quartile 3	MPG Quartile 4	Price change Quar 1 to 4
1	Region	–	–	-3454** (70)	-2923** (98)	-2105** (68)	-1258** (43)	$2196
2	Region	–	Month-of-year	-3773** (80)	-3240** (108)	-2428** (77)	-1589** (55)	$2184
3	Region	Year × Segment	Month-of-year	-1197** (42)	-118+ (63)	436** (39)	720** (49)	$1917
4	–	–	Month-of-year × Region	-3796** (82)	-3263** (111)	-2454** (79)	-1610** (58)	$2186
5	–	Year × Segment	Month-of-year × Region	-1185** (41)	-106+ (59)	450** (36)	734** (45)	$1919
6 (Base)	–	Year × Segment × PADD	Month-of-year × Region	-1182** (42)	-101 (62)	468** (36)	763** (44)	$1945
7	–	Year × Segment × PADD, Year × Trend	Month-of-year × Region	-1264** (41)	-181** (59)	388** (33)	693** (41)	$1957
8	–	Quarter × Segment × PADD	Month-of-year × Region	-1552** (59)	-355** (75)	377** (47)	781** (55)	$2333
9	–	Month × Segment × PADD	Month-of-year × Region	-1759** (178)	-513** (194)	321+ (182)	804** (188)	$2563

* significant at 5%; ** significant at 1%; + significant at 10% level. SEs (robust and clustered at the DMA level) in parentheses.

is row 9, which estimates a fixed effect for each month of the sample separately for each region of the country; this approach taxes the data quite heavily, and the estimated effects, while not wildly different in magnitude from those in the other rows, are no longer statistically significant.

7.2 Future vs. current gasoline prices

In the results we have presented so far, we have estimated the effect of current gasoline prices on the market outcomes from new and used cars. One might argue that since cars are durable goods, buyers should make decisions in response to their *expectations of future gasoline prices*, rather than current gasoline prices. There are several justifications for using current gasoline prices as our explanatory variable of interest. First, it may be the case that car buyers are not sophisticated in thinking about expectations, and that they instead respond to the price that they see posted prominently at gas stations and hear discussed in the news media. Second, if gasoline prices are a random walk, then the expected future gasoline price *is* the current gasoline price. With respect to this point, Anderson, Kellogg, and Sallee (2011) use a set of questions on the Michigan Survey of Consumers that ask explicitly about consumers' gasoline price expectations to show that consumers' average forecast is for "no change in real gasoline prices." This would suggest that our empirical approach, by using current prices, may indeed estimate the response to consumers' expectations of real gasoline prices. This also supports our interpretation of the consumer myopia results as measuring the implied discount rate that rationalizes the current change in car prices with the change in future fuel costs implied by a change in the future real price of gasoline.

Table 10: Effect of time and seasonal fixed effects in market share specification†

	Region FE	Time FE	Seasonal FE	MPG Quartile 1	MPG Quartile 2	MPG Quartile 3	MPG Quartile 4
New Cars							
1	Region	–	–	-.05** (.0044)	-.0062 (.0047)	-.0055+ (.0031)	.061** (.0058)
2	Region	–	Month-of-year	-.049** (.0043)	-.0056 (.0046)	-.005+ (.003)	.059** (.0056)
3	Region	Year	Month-of-year	-.052** (.0051)	-.016** (.0058)	-.003 (.0034)	.071** (.0077)
4	–	–	Month-of-year × Region	-.048** (.0042)	-.0053 (.0043)	-.0041 (.003)	.058** (.0051)
5	–	Year	Month-of-year × Region	-.053** (.0046)	-.016** (.0051)	-.00038 (.003)	.07** (.006)
6 (Base)	–	Year × Region	Month-of-year × Region	-.057** (.0048)	-.014** (.004)	.0002 (.0027)	.071** (.0058)
7	–	Year × Region Year × Trend	Month-of-year × Region	-.049** (.005)	-.025** (.0034)	-.00084 (.0034)	.075** (.0043)
8	–	Quarter × Region	Month-of-year × Region	-.07** (.0069)	-.029** (.0056)	.012** (.0047)	.087** (.0065)
9	–	Month × Region		-.12+ (.068)	-.013 (.04)	.036 (.03)	.097 (.078)

* significant at 5%; ** significant at 1%; + significant at 10% level. SEs (robust and clustered at the DMA level) in parentheses.

In this section, we take an alternative approach, which is to make use of the active futures market for crude oil to create a measure of consumers' expectations of future gasoline prices. While futures contracts for gasoline are listed on the NYMEX, futures in oil are actively traded in much larger volumes. Furthermore, gasoline prices are sufficiently closely correlated with oil prices that we suspect that a gasoline price forecast based on futures prices for oil will be a better measure of expectations of gasoline prices than using gasoline futures prices directly.

To be precise, we regress monthly, DMA-level gasoline prices on current, world prices for crude oil, and on DMA times month-of-year fixed effects. This allows us to translate the price of a barrel of oil into the price for a gallon of gasoline, allowing the "markup" between these two to vary by region, and by season differentially for each region. (This allows, for example, for refinery margins that vary geographically and seasonally.) We use the estimated coefficients from this regression to predict an expected future price for gasoline by using alternately the 6-month-ahead, 12-month-ahead, and 24-month-ahead futures price for crude oil in place of the current price of oil. We then use our prediction of the expected future price of gasoline in place of the current price of gasoline in our benchmark specifications for new and used car prices and new car market shares. The results using our prediction of the expected future price of gasoline are reported in Tables A-8 and A-9.

The estimated results for the new car market share are very similar whether we use current gasoline prices or our prediction of expected future gasoline prices. For the estimate of the effect of gasoline prices on car prices, using our prediction of the expected future gasoline prices yields relative price effects that are 61% - 87% larger in magnitude for new cars and 17% - 19% larger in magnitude for used cars than using the current gasoline price. These results imply that consumers adjust their willingness-to-pay *more* in response to changes in future fuel costs than is reflected in the estimates used to produce Table 7. Using the estimates from Tables A-8 and A-9 would generate lower implied discount rates than what is reported in Table 7, corresponding to less myopia among car buyers.

7.3 Heterogeneity in gasoline price response

Our base specifications estimated a single coefficient on *GasolinePrice* for each quartile, disallowing other types of response heterogeneity to gasoline prices. In this subsection, we investigate two types of heterogeneity that might exist. First, we investigate whether, for example, a $1 increase in gasoline prices has a different effect on car prices and market shares when gasoline currently costs $1.50 per gallon from when it costs $3.50 per gallon. Second, we investigate whether the response to gasoline price differs by whether gasoline prices have been consistently rising or falling in prior periods.

To answer the first question we repeat the main results in Section 4 using *GasolinePrice* interacted with indicators for whether the gasoline price lies in the range <$1.50, $1.50-$2.50, $2.50-$3.50, or >$3.50. The purpose is to see whether there is an inflection point of gasoline prices at which the effects suddenly kick in, or at which they grow much larger. News reports have posited that there is a gasoline price "threshold" above which consumers change their behavior more dramatically.[47] Our market share results are fairly similar across different ranges of gasoline prices, except that when gasoline prices are above $3.50, new car buyers shift into quartile 4 cars at a slightly higher rate, and into quartile 3 cars at a much lower rate, than when gasoline prices are lower. The effect of gasoline prices on the relative prices of cars of different fuel economies, both new and used, is also pretty similar across the range of gasoline prices; the effect is bigger for the relative prices of new cars when gasoline is above $3.50 per gallon. See Tables A-10 and A-11 for a summary of these results; full results are available from the authors.

To answer the second question we also repeat the main results of this section interacting *GasolinePrice* with an indicator variable that records whether gasoline prices went up monotonically in the previous three months, went down monotonically in the previous three months, or had a non-monotonic pattern. These results show some heterogeneity in the gasoline price response, although not enough to change the conclusions of the paper. The greatest heterogeneity is in the effect of

[47]For example, an article in Automotive News on 5/22/08 entitled "Ford: $3.50 gasoline was tipping point for sales shift" states: "The segment shifts [away from SUVs and Pickups] 'really started to move' when gasoline prices hit $3.50 a gallon, [Ford CEO Alan] Mulally said. 'It seemed to us that we reached a tipping point where customers began shifting away from these vehicles at an accelerated rate,'...."

gasoline price changes on used car prices. The results imply that a change in the price of gasoline has a larger effect on the relative prices of high vs. low fuel economy cars when gasoline prices have been trending down than when they have been trending up or have been neither trending up nor down. See Tables A-12 and A-13 for a summary of these results; full results are available from the authors.

7.4 Gasoline price aggregation

Next, we investigate the robustness of our findings to the aggregation of gasoline prices to local markets (DMAs) rather than to ZIP-codes, which would be possible in our data. The advantage of using the higher level of aggregation is that we reduce the possibility of measurement error that could arise from our observing only a small number of stations per ZIP-code. The higher level of aggregation also allows for consumers to react not only to the gasoline prices in their local ZIP-code but also to gasoline prices in a broader area. At the same time, however, we eliminate some of the cross-sectional variation that less aggregate data would allow us to use.

One could also make the argument that we should use a more aggregate measure of gasoline prices than DMA-level prices because consumers may notice gasoline price changes only once they have affected a large enough area to be reported in the media, or because local price variation contains transitory price shocks that do not enter into long-run forecasts of gasoline prices.

To investigate whether our conclusions depend of the level of aggregation of gasoline prices, we re-estimate our original car price and market share specifications (Equations 2, 3, and 5) using a less aggregated and a more aggregated measure of gasoline prices. We use 4-digit ZIP-code level gasoline price as our less aggregated measure.[48] For our more aggregated measure, we average the prices for basic grade over all stations in each "Petroleum Administration for Defense District" (PADD). PADDs are the standard geographical classification used by the Energy Information Administration, defined such that they delineate a region in which gasoline supply is homogenous. There are five PADDs: East Coast, Midwest, Gulf Coast, Rockies, and West Coast. There remains substantial variation in gasoline prices between PADDs and across PADDs over time.

The full results are reported in Tables A-14 and A-15. We find that the coefficients on gasoline prices in the 4-digit ZIP code aggregation are similar to those in our (original) DMA aggregation but somewhat smaller in magnitude. This is consistent with some measurement error occurring in the 4-digit ZIP code aggregation. If we aggregate gasoline prices at the PADD level, most coefficient estimates in the market share regression are unchanged. In the price regression, the PADD-level

[48] We use this instead of 5-digit ZIP-code level price because too many 5-digit ZIP-codes have too few gas stations to calculate a reliable average. In our data, the median 4-digit ZIP code reports data from 11.5 stations on average over the months of the year, up from 3 for 5-digit ZIP codes.

estimates are distinctly larger in magnitude than the estimates using DMA-level prices.

Overall, we would reach many of the same conclusions about the effects of gasoline price changes if we aggregated gasoline prices within 4-digit ZIP code or within PADD instead of within DMAs.

7.5 Endogeneity

So far we have assumed that gasoline prices are uncorrelated with the error term in the market share and price specifications. In this subsection, we relax that assumption.

It seems unlikely that such a correlation would arise due to reverse causality; U.S. gasoline prices are determined by world oil prices and refinery margins, and these are unlikely to be influenced by car transactions in the U.S. However, there are other potential sources of endogeneity which could taint our coefficient estimates. First, there could be local variations in economic conditions that are correlated with local variations in gasoline prices. If the changes in economic conditions change what cars people buy or how much they are willing to spend on them, then our gasoline price coefficients will capture (in part) cyclical effects on car sales and prices. Second, gasoline tax changes might be endogenous to economic conditions which also affect car sales and prices. Third, changes in gasoline prices could cause income shocks in local areas (say, areas with refineries or with car plants) and these income shocks may drive car sales and prices.

One way to address the potential endogeneity of gasoline prices would be to use a more aggregate measure of gasoline price; this would make it less likely that local shocks lead to correlation between gasoline prices and the error term in the market share and price specifications. The specification using PADD-level gasoline prices (described in the previous section and reported in Tables A-14 and A-15) does exactly this.

A second approach we take is to use world oil price as an instrument for gasoline prices at the PADD level. Clearly, world oil prices are correlated with regional fuel prices. At the same time, it seems highly unlikely that local or regional variation in economic conditions, gasoline tax changes, or income shocks would have a meaningful effect on world oil prices. To allow for some variation by PADD in the correlation with world oil prices, we use as instruments world oil prices interacted with PADD dummies. The results of these two approaches are reported in Tables A-16 and A-17.

We have already concluded that the OLS regression with PADD-level gasoline prices estimates similar market share effects but somewhat larger price effects compared to the original OLS regression with DMA-level gasoline prices. The PADD-level IV estimates of the effect of gasoline prices on market share are about 10% larger than the PADD-level OLS estimates for the lowest fuel economy quartile, and about 15% smaller for the highest fuel economy quartile. We find that the estimates of the effect of gasoline prices on car prices are generally larger in the PADD-level IV specification than in the PADD-level OLS specification. This can be seen in Table A-17.

In summary, controlling for endogeneity suggests that our original specification may have underestimated the magnitude of the gasoline price effect on car prices. Using the PADD-level IV estimates in our myopia calculations would lead to smaller implied discount rates—implying consumers who value the future more—than what is reported in Table 7.

7.6 Alternative market share specification

As our last robustness check we address potential limitations of the linear probability model we have used to estimate the effect of gasoline prices on markets shares. One might be concerned that the linear probability model does not constrain the estimates in the market share regressions to add up to 1.[49] To address this we reestimate our basic market share specification (Equation 5) with a multinomial logit ("mlogit" in Stata) which estimates the probability that, conditional on purchase, a car falls into MPG Quartile 1, 2, 3, or 4. (All variables and controls are the same as those specified in Equation 5.) Full estimation results are reported in Table A-18.

The marginal effects in probability associated with a $1 increase in gasoline prices as estimated by the multinomial logit are slightly larger than in the linear probability model (-0.064** vs. -0.057** for MPG quartile 1, -0.014 vs. -0.014 for MPG quartile 2, -0.004 vs. 0.0002 for MPG quartile 3, and 0.075** vs. 0.071** for MPG quartile 4, where ** indicates estimates that are statistically significiant at the 1% level). We conclude that our market share results do not depend on our use of the linear probability model.

8 Concluding remarks

In this paper we have estimated the effect of gasoline prices on the short-run equilibrium prices, market shares, and sales of new and used cars of different fuel economies. We have used these estimates to address two questions that are important for understanding the ability of a policy intervention such as a gasoline tax or a carbon tax to influence what cars people buy, which is one avenue through which such an intervention can affect greenhouse gas emissions.[50]

We estimated that a $1 increase in the price of gasoline increases the market share of cars in the highest fuel economy quartile by 21.1% and decreases the market share of cars in the lowest fuel economy quartile by 27.1%. We also estimated the effect of a $1 increase in gasoline prices on unit sales of new cars and found that sales in the highest fuel economy quartile increased by 10–12%, while sales in the lowest fuel economy quartile fell by 27–28%. We estimated the effect

[49] In fact, the market shares predicted by the linear probability results in Section 4.5 come very close to summing to 1, despite no constraint to do so.

[50] Other potential avenues including changing vehicle miles travelled, car designs, fuel technologies, or urban design.

of gasoline prices on the equilibrium prices of new cars and found that a $1 increase in the price of gasoline is associated with an increase of $354 in the average price of the highest fuel economy quartile of cars relative to that of the lowest fuel economy quartile. For used cars, the estimated relative price difference is $1,945.

The first question we addressed is whether the changes in equilibrium prices for new and used cars associated with changes in gasoline prices show evidence that consumers undervalue future gasoline costs of cars with different fuel economies relative to the prices of those cars. This could be thought of as a necessary "demand side" condition for effective policy: the more car buyers discount future fuel costs, the less effective a gasoline tax or carbon tax will be in influencing vehicle choice. Using several different assumptions about vehicle miles travelled, a range of assumptions about the elasticity of demand, and comparing the relative price differences between different quartiles, we find little evidence of consumer myopia. Many of our implied discount rates are near zero, most are less than 20%.[51]

The second question we addressed is whether gasoline prices have similar effects in new and used markets. This could be thought of as a "supply side" necessary condition for effective policy: actions that car manufacturers take that counteract the effect of gasoline prices will reduce the effectiveness of a gasoline tax or carbon tax in influencing vehicle choice. We find very different equilibrium effects in new and used markets; a gasoline price increase has a much larger effect on prices in the used car market than in the new car market, but has a substantial effect on sales in the new car market. We argued that these differences can be explained by differences in supply between new and used markets. A general implication of this point is that when designing policy, policymakers need to take into account the market structure of the markets whose outcome they wish to influence.

Forecasting the effect of policy interventions such as a carbon tax or a gasoline tax increase on greenhouse gas emissions from non-commercial vehicles is challenging because there are many possible margins of adjustment. We believe that our investigation of the effect of gasoline price on market outcomes in new and used car markets is useful for understanding some of these margins. While our paper is not the only one to address these issues, we believe our paper's particular advantages are that it uses transaction data; that the data on prices and quantities and on new and used markets are from the same source; and that the flexible specifications used allow us to estimate parameters whose interpretation is not dependent on a particular model of the data generating process and which can be combined with a range of assumptions about related parameters in order to answer policy-relevant questions.

[51]The alternative specifications we investigated in Section 7 generally led to larger relative price effect estimates, which would reduce the estimated implied discount rates compared to what is reported in Table 7.

References

Allcott, H., and N. Wozny (2011): "Gasoline Prices, Fuel Economy, and the Energy Paradox," Discussion paper, New York University.

Anderson, S. T., R. Kellogg, and J. M. Sallee (2011): "What Do Consumers Believe about Future Gasoline Prices?," Discussion Paper 215, Energy Institute at Haas.

Berry, S., J. Levinsohn, and A. Pakes (1995): "Automobile Prices in Market Equilibrium," *Econometrica*, 63(4), 841–890.

Blomqvist, A. G., and W. Haessel (1978): "Small Cars, Large Cars, and the Price of Gasoline," *The Canadian Journal of Economics/Revue canadienne d'Economique*, 11(3), 470–489.

Bresnahan, T. F., and V. A. Ramey (1994): "Output Fluctuations at the Plant Level," *Quarterly Journal of Economics*, 109(3), 593–624.

Busse, M. R., and N. O. Keohane (2007): "Market Effects of Environmental Regulation: Coal, Railroads, and the 1990 Clean Air Act," *RAND Journal of Economics*, 38(4), 1159–1179.

Busse, M. R., and J. Silva-Risso (2010): ""One Discriminatory Rent" or "Double Jeopardy": Multi-componnet Negotiation for New Car Purcahases," *American Economic Review*, 100(2), 470–474.

Busse, M. R., J. Silva-Risso, and F. Zettelmeyer (2006): "\$1000 Cash Back: The Pass-Through of Auto Manufacturer Promotions," *American Economic Review*, 96(4), 1253–1270.

Carlson, R. L. (1978): "Seemingly Unrelated Regression and the Demand for Automobiles of Different Sizes, 1965-1975: A Disaggregate Approach," *The Journal of Business*, 51(2), 243–262.

Davis, L. W., and M. Kahn (2010): "International Trade in Used Vehicles: The Environmental Consequences of NAFTA," *American Economic Journal: Economic Policy*, 2(4), 58–82.

Donna, J. (2010): "The Effect of Gasoline Prices on Urban Travel Demand: Evidence from Chicago," Discussion paper, Northwestern University.

Espey, M., and S. Nair (2005): "Automobile Fuel Economy: What is it Worth?," *Contemporary Economic Policy*, 23(3), 317–323.

Fowlie, M. (2010): "Emissions Trading, Electricity Restructuring, and Investment in Pollution Abatement," *American Economic Review*, 100, 837–869.

Goldberg, P. K. (1995): "Product Differentiation and Oligopoly in International Markets: The Case of the U.S. Automobile Industry," *Econometrica*, 63(4), 891–951.

——— (1998): "The Effects of the Corporate Average Fuel Efficiency Standards in the US," *Journal of Industrial Economics*, 46(1), 1–33.

Gramlich, J. (2009): "Gas Prices, Fuel Efficiency, and Endogenous Product Choice in the U.S. Automobile Industry," Discussion paper, Georgetown University.

Greenlees, J. S. (1980): "Gasoline Prices and the Purchases of New Automobiles," *Southern Economic Journal*, 47(1), 167–178.

Hausman, J. A. (1979): "Individual Discount Rates and the Purchase and Utilization of Energy-Using Durables," *The Bell Journal of Economics*, 10(1), 33–54.

Hughes, J. E., C. R. Knittel, and D. Sperling (2008): "Evidence of a Shift in the Short-Run Price Elasticity of Gasoline Demand," *Energy Journal*, 29(1).

Jacobsen, M. R. (2010): "Evaluating U.S. Fuel Economy Standards In a Model with Producer and Household Heterogeneity," Discussion paper, University of California, San Diego.

Kahn, J. (1986): "Gasoline Prices and the Used Automobile Market: A Rational Expectations Asset Price Approach," *Quarterly Journal of Economics*, 101(2), 323–340.

Kilian, L., and E. R. Sims (2006): "The Effects of Real Gasoline Prices on Automobile Demand: A Structural Analysis Using Micro Data," Discussion paper, University of Michigan.

Klier, T., and J. Linn (forthcoming): "The Price of Gasoline and New Vehicle Fuel Economy: Evidence from Monthly Sales Data," *American Economic Journal: Economic Policy.*

Knittel, C. R. (2009): "Automobiles on Steroids: Product Attribute Trade-offs and Technological Progress in the Automobile Sector," Working Paper 15162, National Bureau of Economic Research.

Knittel, C. R., and R. Sandler (2010): "Carbon Prices and Automobile Greenhouse Gas Emissions: The Extensive and Intensive Margins," Working Paper 16482, National Bureau of Economic Research.

Li, S., C. Timmins, and R. von Haefen (2009): "How Do Gasoline Prices Affect Fleet Fuel Economy?," *American Economic Journal: Economic Policy*, 1(2), 113–137.

Lu, S. (2006): "Vehicle Survivability and Travel Mileage Schedules," Working Paper DOT HS 809 952, NHTSA Technical Report.

Mansur, E. T. (2007): "Do Oligopolists Pollute Less? Evidence from a Restructured Electricity Market," *Journal of Industrial Economics*, 55(4), 661–689.

Ohta, M., and Z. Griliches (1986): "Automobile Prices and Quality: Did the Gasoline Price Increases Change Consumer Tastes in the U.S.?," *Journal of Business and Economic Statistics*, 4(2), 187–198.

Sallee, J. M., S. E. West, and W. Fan (2009): "Consumer Valuation of Fuel Economy: A Microdata Approach," Discussion paper, National Tax Association Conference Proceedings.

Sawhill, J. W. (2008): "Are Capital and Operating Costs Weighted Equally in Durable Goods Purchases? Evidence from the US Automobile Market," Working paper, University of California, Berkeley.

Tishler, A. (1982): "The Demand for Cars and the Price of Gasoline: The User Cost Approach," *The Review of Economics and Statistics*, 64(2), 184–190.

Verboven, F. (1999): "Product Line Rivalry and Market Segmentation–With an Application to Automobile Optional Engine Pricing," *Journal of Industrial Economics*, 47(4), 399–425.

West, S. E. (2007): "The Effect of Gasoline Prices on the Demand for Sport Utility Vehicles," Working paper, Macalester College.

Table 11: Summary Statistics

	New Cars						Used Cars					
Variable	N	Mean	Median	SD	Min	Max	N	Mean	Median	SD	Min	Max
GasolinePrice	1863403	2	1.8	.67	.82	4.6	1096874	2	1.8	.69	.82	4.6
MPG	1863403	22	22	5.7	10	65	1096874	22	22	4.7	9.8	65
Price	1863403	25515	23295	10874	2576	195935	1096874	15637	14495	8281	1	173000
DaysToTurn	1798625	57	27	76	1	730	1058521	48	26	66	1	730
ModelYear	1863403	2004	2004	2.5	1997	2008	1096874	2001	2001	3.5	1985	2008
CarAge	1863403	.79	1	.46	0	3	1096874	3.9	4	2.4	0	24
TradeValue	795457	8619	6794	8107	0	198000	435813	5233	3000	5992	0	150000
PctWhite	1863403	.72	.82	.26	0	1	1096874	.7	.81	.28	0	1
PctBlack	1863403	.082	.024	.16	0	1	1096874	.11	.028	.2	0	1
PctAsian	1863403	.05	.02	.087	0	1	1096874	.038	.013	.07	0	1
PctHispanic	1863403	.12	.053	.18	0	1	1096874	.13	.05	.19	0	1
PctLessHighSchool	1863403	.15	.12	.13	0	1	1096874	.18	.14	.13	0	1
PctCollege	1863403	.38	.36	.19	0	1	1096874	.33	.29	.18	0	1
PctManagment	1863403	.16	.15	.082	0	1	1096874	.14	.13	.074	0	1
PctProfessional	1863403	.22	.22	.097	0	1	1096874	.2	.19	.092	0	1
PctHeath	1863403	.016	.012	.018	0	1	1096874	.019	.014	.02	0	1
PctProtective	1863403	.02	.016	.021	0	1	1096874	.021	.017	.021	0	1
PctFood	1863403	.041	.035	.031	0	1	1096874	.046	.04	.033	0	1
PctMaintenance	1863403	.028	.021	.029	0	1	1096874	.032	.025	.031	0	1
PctHousework	1863403	.027	.024	.021	0	1	1096874	.028	.025	.022	0	1
PctSales	1863403	.12	.12	.046	0	1	1096874	.12	.11	.044	0	1
PctAdmin	1863403	.15	.15	.054	0	1	1096874	.16	.16	.054	0	1
PctConstruction	1863403	.049	.042	.039	0	1	1096874	.056	.049	.041	0	1
PctRepair	1863403	.036	.033	.027	0	1	1096874	.04	.037	.027	0	1
PctProduction	1863403	.063	.049	.053	0	1	1096874	.075	.061	.059	0	1
PctTransportation	1863403	.05	.044	.037	0	1	1096874	.059	.053	.039	0	1
Income	1863403	58110	53188	26274	0	200001	1096874	50684	46556	22031	0	200001
MedianHHSize	1863403	2.7	2.7	.52	0	9	1096874	2.7	2.7	.51	0	8.5
MedianHouseValue	1863403	178306	144700	131956	0	1000001	1096874	145545	121997	102923	0	1000001
VehPerHousehold	1863403	1.8	1.9	.39	0	7	1096874	1.8	1.8	.39	0	7
PctOwned	1863403	.72	.8	.23	0	1	1096874	.69	.76	.24	0	1
PctVacant	1863403	.063	.042	.078	0	1	1096874	.067	.048	.076	0	1
TravelTime	1863403	27	27	6.8	0	200	1096874	27	26	6.9	0	200
PctUnemployed	1863403	.047	.037	.043	0	1	1096874	.053	.041	.046	0	1
PctBadEnglish	1863403	.044	.016	.078	0	1	1096874	.045	.014	.079	0	1
PctPoverty	1863403	.084	.057	.085	0	1	1096874	.1	.072	.095	0	1
Weekend	1863403	.25	0	.44	0	1	1096874	.25	0	.44	0	1
EndOfMonth	1863403	.25	0	.43	0	1	1096874	.21	0	.41	0	1
EndOfYear	1863403	.022	0	.15	0	1	1096874	.017	0	.13	0	1

NOT FOR PUBLICATION

Appendix: Additional Tables

Table A-1: New car fuel economy quartile cutoffs

Modelyear	MPG Q1 Mean	25th Pctile	MPG Q2 Mean	50th Pctile	MPG Q3 Mean	75th Pctile	MPG Q4 Mean
1997	16.3	18.6	20.1	21.3	23.0	24.7	27.7
1998	16.1	17.9	19.6	21.3	22.6	24.3	27.2
1999	15.8	17.9	19.6	21.6	22.7	24.3	27.2
2000	15.9	17.9	19.4	20.9	22.5	24.0	27.2
2001	15.7	17.2	18.9	20.6	22.1	23.7	27.2
2002	15.6	17.2	18.9	20.6	22.0	23.3	27.1
2003	15.5	17.2	19.0	20.6	22.2	23.5	27.5
2004	16.0	17.6	19.1	20.6	22.2	24.0	27.9
2005	15.9	17.9	19.3	20.9	22.2	24.0	27.8
2006	16.1	17.6	18.9	20.6	22.0	23.8	27.7
2007	16.8	18.3	19.9	21.3	22.8	25.0	28.8
2008	16.6	18.9	20.0	21.6	23.2	25.4	29.5

Table A-2: New Cars: Price results, fuel economy quartiles†

Variable	Coefficient/SE
FuelPrice*MGP Quart 1	-250** (72)
FuelPrice*MGP Quart 2	-96** (37)
FuelPrice*MGP Quart 3	-11 (26)
FuelPrice*MGP Quart 4	104* (47)
PctLessHighSchool	163+ (83)
PctCollege	-51 (58)
Income	.0015** (.00044)
MedianHHSize	43** (16)
MedianHouseValue	.00012 (.000084)
VehiclePerHH	402** (120)
TravelTime	-.82 (1.1)
Weekend	-13* (6)
EndOfMonth	-135** (4.3)
EndOfYear	-78** (17)
Constant	27246** (79)
Observations	1863403
R-squared	0.053

* significant at 5%; ** significant at 1%; + significant at 10% level. SEs (robust and clustered at the DMA level) in parentheses. Not reported: Region × year, region × month-of-year fixed effects, car type, and car age fixed effects. We also don't report house ownership, occupation, english proficiency, and race of buyers.

Table A-3: Used Cars: Price results, fuel economy quartiles†

Variable	Coefficient/SE
FuelPrice*MGP Quart 1	-1182**
	(42)
FuelPrice*MGP Quart 2	-101
	(62)
FuelPrice*MGP Quart 3	468**
	(36)
FuelPrice*MGP Quart 4	763**
	(44)
PctLessHighSchool	239**
	(69)
PctCollege	-4.5
	(50)
Income	.0017**
	(.0005)
MedianHHSize	26
	(22)
MedianHouseValue	.000056
	(.00014)
VehiclePerHH	162
	(157)
TravelTime	.27
	(.72)
Weekend	120**
	(10)
EndOfMonth	-71**
	(6.3)
EndOfYear	-18
	(23)
Constant	24010**
	(252)
Observations	1096874
R-squared	0.718

* significant at 5%; ** significant at 1%; + significant at 10% level. SEs (robust and clustered at the DMA level) in parentheses. Not reported: Region × year, region × month-of-year fixed effects, car type, and odometer spline. We also don't report house ownership, occupation, english proficiency, and race of buyers.

Table A-4: New Cars: Market share results, fuel economy quartiles†

	MPG Quartile 1	MPG Quartile 2	MPG Quartile 3	MPG Quartile 4
FuelPrice	-.057**	-.014**	.0002	.071**
	(.0048)	(.004)	(.0027)	(.0058)
PctLessHighSchool	.044**	.031**	-.027*	-.047*
	(.015)	(.0089)	(.013)	(.02)
PctCollege	-.061**	.0079	.0033	.05**
	(.013)	(.011)	(.013)	(.018)
Income	-5.9e-08	3.4e-07**	3.0e-07**	-5.8e-07**
	(8.7e-08)	(9.4e-08)	(1.1e-07)	(1.2e-07)
MedianHHSize	.01**	.0048+	-.0067	-.0083+
	(.0029)	(.0025)	(.0048)	(.0047)
MedianHouseValue	7.2e-08*	3.3e-08+	1.3e-08	-1.2e-07**
	(2.9e-08)	(1.7e-08)	(8.7e-09)	(3.7e-08)
VehiclePerHH	.016	-.015	.042	-.043
	(.022)	(.022)	(.026)	(.033)
TravelTime	-.0002	-.00037**	-.00025*	.00082**
	(.00019)	(.000098)	(.00013)	(.00022)
Weekend	-.02**	-.0046**	-.0022	.027**
	(.0019)	(.0016)	(.0016)	(.0022)
EndOfMonth	.0058**	.0033**	.0048**	-.014**
	(.00099)	(.0011)	(.001)	(.0012)
EndOfYear	-.0043	-.0058**	-.0013	.011**
	(.0027)	(.0022)	(.0028)	(.004)
Constant	.33**	.23**	.27**	.18**
	(.017)	(.013)	(.01)	(.018)
Observations	1863403	1863403	1863403	1863403
R-squared	0.034	0.011	0.009	0.040

* significant at 5%; ** significant at 1%; + significant at 10% level. SEs (robust and clustered at the DMA level) in parentheses.
Not reported: Region × year, region × month-of-year, and car age fixed effects. We also don't report house ownership, occupation, english proficiency, and race of buyers.

Table A-5: Used Cars: Transaction share results, fuel economy quartiles†

	MPG Quartile 1	MPG Quartile 2	MPG Quartile 3	MPG Quartile 4
FuelPrice	.00018 (.0069)	-.0077 (.0058)	.017 (.011)	-.009 (.0074)
PctLessHighSchool	.006 (.01)	.023+ (.012)	-.018 (.024)	-.011 (.02)
PctCollege	-.016 (.01)	-.02 (.014)	-.022 (.015)	.058** (.014)
Income	-2.0e-07* (8.7e-08)	2.6e-07** (8.2e-08)	2.7e-07* (1.1e-07)	-3.3e-07** (9.7e-08)
MedianHHSize	.0018 (.0024)	-.0042+ (.0024)	.0041 (.0034)	-.0018 (.0027)
MedianHouseValue	2.0e-08 (1.3e-08)	2.0e-08+ (1.1e-08)	-7.6e-08** (1.6e-08)	3.6e-08** (1.3e-08)
VehiclePerHH	.0037 (.026)	.03 (.031)	-.11* (.055)	.08 (.053)
TravelTime	.000029 (.00013)	-.00016 (.00013)	-.00011 (.00018)	.00023 (.00019)
Weekend	-.0076** (.0014)	-.0042* (.0019)	.0056* (.0022)	.0062** (.0019)
EndOfMonth	.0038+ (.0021)	-.0051** (.0018)	.0019 (.0021)	-.00061 (.0019)
EndOfYear	-.011** (.0028)	.0042 (.0036)	.00083 (.0036)	.0059* (.0029)
Constant	.014 (.02)	.027 (.018)	-.031 (.026)	.99** (.017)
Observations	1096874	1096874	1096874	1096874
R-squared	0.485	0.224	0.235	0.531

* significant at 5%; ** significant at 1%; + significant at 10% level. SEs (robust and clustered at the DMA level) in parentheses.
Not reported: Region × year, region × month-of-year, and car age fixed effects. We also don't report house ownership, occupation, english proficiency, and race of buyers.

Figure A-1: Crude spot and futures prices during our sample

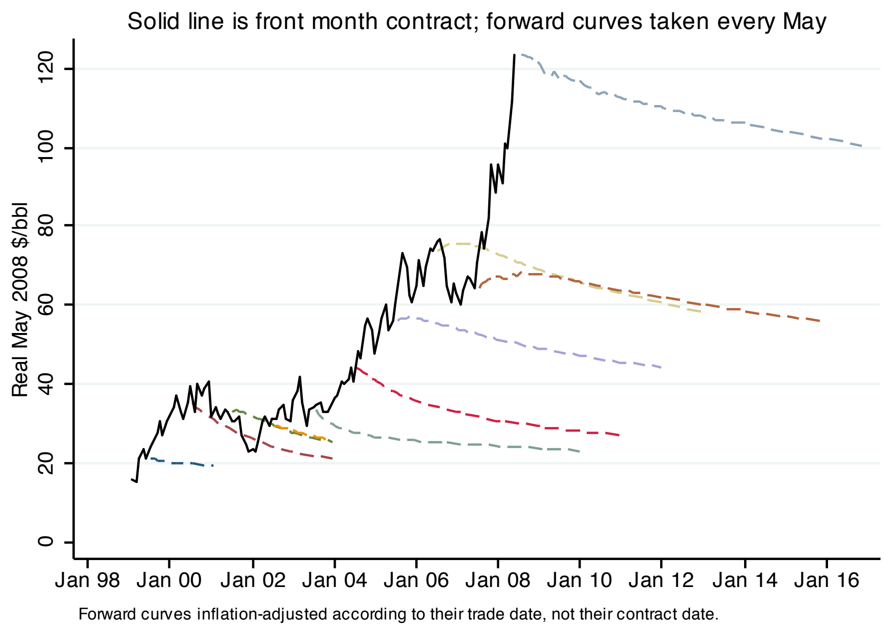


Table A-6: New and Used Cars: Inventory results†

	New Cars			Used Cars		
Variable	Coefficient (SE)	DTT sample mean	% Change in DTT	Coefficient (SE)	DTT sample mean	% Change in DTT
GasolinePrice * Quart. 1 (lowest fuel economy)	12** (1.9)	67.7	17.7%	.95+ (.56)	46.9	2.0%
GasolinePrice * Quart. 2	2* (.8)	60.7	3.3%	1.2+ (.67)	46.2	2.6%
GasolinePrice * Quart. 3	1.5* (.7)	57.7	2.6%	.053 (.65)	48.0	0.1%
GasolinePrice * Quart. 4 (highest fuel economy)	-5.5** (.7)	48.9	-11.5%	-1.9** (.59)	43.9	-4.3%

† This table only reports the coefficients on gasoline prices. The full specification for both new and used cars is:

$$DTT_{irdjt} = \omega_0 + \omega_1(\text{GasolinePrice}_{it} \cdot \text{MPG Quartile}_j) + \omega_2\text{Demog}_{it} + \omega_3\text{PurchaseTiming}_{jt} + \delta_{dj} + \tau_{rt} + \mu_{rt} + \nu_{ijt}$$

where DTT_{irdjt} measures days to turn for transaction i in region r at dealer d on date t for car j. We use the same extensive set of controls we have used in the market share specification (see page 10) with one addition. To control for the fact that different dealerships may have different inventory policies we include car type × dealer fixed effects (δ_{dj}).

* significant at 5%; ** significant at 1%; + significant at 10% level. SEs (robust and clustered at the DMA level) in parentheses.

Table A-7: New and Used Cars: Actual cash value of trade-in†

	New Car Trade-in Actual Cash Value	Used Car Trade-in Actual Cash Value	Used Car Transaction Prices
GasolinePrice*MPG Quart 1	-1109**	-683**	-1182**
	(40)	(39)	(42)
GasolinePrice*MPG Quart 2	-77+	-5.6	-101
	(40)	(43)	(62)
GasolinePrice*MPG Quart 3	364**	158**	468**
	(37)	(34)	(36)
GasolinePrice*MPG Quart 4	447**	92*	763**
	(41)	(39)	(44)

† This table only report the coefficients on gasoline prices. The full specification for both new and used cars in columns 1 and 2 is:

$$\text{ACV}_{ilrt} = \beta_0 + \beta_1 \text{GasolinePrice}_{it} \cdot \text{MPG Quartile}_l + \beta_2 \text{Odometer}_{ilt} + \beta_3 \text{Demog}_{it} + \beta_4 \text{PurchaseTiming}_{jt} + \delta_l + \tau_{rt} + \mu_{rt} + \xi_{ilrt}$$

where ACV_{ilrt} is the actual cash value booked in transaction i for trade-in car l in region r on date t. We add a new control variable to this specification, which is the odometer reading of the trade-in car; cars with higher odometer readings have experienced greater depreciation and should be booked at lower actual cash values, all else equal. In the specification, we include the demographic characteristics of the buyer; these should not have a direct effect on the average cash value, but may be correlated with unobservable quality characteristics ("wear and tear") of the trade-in car. We also include the purchase timing of the transaction, in case cars are assigned different actual cash values on, for example, weekend days, when there is typically higher transaction volume. Finally, we include detailed "car type" fixed effects for the trade-in, as well as our region-specific year and region-specific month-of-year fixed effects.

* significant at 5%; ** significant at 1%; + significant at 10% level. SEs (robust and clustered at the DMA level) in parentheses.

Table A-8: Effect of predicted gasoline price expectations in price regression†

Gas Price Variable	MPG Quartile 1	MPG Quartile 2	MPG Quartile 3	MPG Quartile 4
New Cars				
Current Price	-250**	-96**	-11	104*
(original specification)	(72)	(37)	(26)	(47)
Gasoline Price Future	-456**	-167**	-56+	113+
Delivery in 6 months	(96)	(48)	(32)	(63)
Gasoline Price Future	-536**	-222**	-92*	86
Delivery in 12 months	(102)	(53)	(36)	(66)
Gasoline Price Future	-583**	-251**	-108**	80
Delivery in 24 months	(106)	(56)	(38)	(68)
Used Cars				
Gas Price Variable	MPG Quartile 1	MPG Quartile 2	MPG Quartile 3	MPG Quartile 4
Current Price	-1182**	-101	468**	763**
(original specification)	(42)	(62)	(36)	(44)
Gasoline Price Future	-1365**	-168*	520**	905**
Delivery in 6 months	(58)	(66)	(40)	(47)
Gasoline Price Future	-1414**	-204**	505**	905**
Delivery in 12 months	(60)	(66)	(42)	(50)
Gasoline Price Future	-1495**	-269**	455**	867**
Delivery in 24 months	(63)	(66)	(44)	(52)

* significant at 5%; ** significant at 1%; + significant at 10% level. SEs (robust and clustered at the DMA level) in parentheses.

Table A-9: Effect of predicted gasoline price expectations in market share regression†

	New Cars			
Gas Price Variable	MPG Quartile 1	MPG Quartile 2	MPG Quartile 3	MPG Quartile 4
Current Price (original specification)	-.057** (.0048)	-.014** (.004)	.0002 (.0027)	.071** (.0058)
Gasoline Price Future Delivery in 6 months	-.065** (.006)	-.0024 (.008)	.0014 (.0041)	.066** (.009)
Gasoline Price Future Delivery in 12 months	-.067** (.0066)	-.0046 (.0096)	.00035 (.0047)	.071** (.01)
Gasoline Price Future Delivery in 24 months	-.062** (.0071)	-.0061 (.011)	-.003 (.0051)	.071** (.012)

* significant at 5%; ** significant at 1%; + significant at 10% level. SEs (robust and clustered at the DMA level) in parentheses.

Table A-10: New Cars: Market share (quartile) results by gasoline price levels†

	New Cars			
	MPG Quartile 1	MPG Quartile 2	MPG Quartile 3	MPG Quartile 4
GasolinePrice (<1.5 dollar)	-.061** (.0064)	-.013* (.0054)	.0072* (.0035)	.067** (.006)
GasolinePrice (1.5-2.5 dollars)	-.065** (.0059)	-.0095* (.0048)	.0088** (.0031)	.065** (.0055)
GasolinePrice (2.5-3.5 dollars)	-.061** (.0053)	-.011** (.0042)	.0075** (.0027)	.065** (.0047)
GasolinePrice (>3.5 dollars)	-.062** (.006)	-.013* (.0059)	-.0043 (.0034)	.079** (.0084)

* significant at 5%; ** significant at 1%; + significant at 10% level. SEs (robust and clustered at the DMA level) in parentheses.
This table only reports the coefficients on gasoline prices.

Table A-11: New and Used Cars: Price results by gasoline price levels†

	New Cars, MPG Quartiles	Used Cars, MPG Quartiles
GasolinePrice(< 1.5)*MPG Quart 1	-274** (83)	-1373** (72)
GasolinePrice(< 1.5)*MPG Quart 2	-186** (59)	-127 (126)
GasolinePrice(< 1.5)*MPG Quart 3	-73+ (39)	825** (71)
GasolinePrice(< 1.5)*MPG Quart 4	51 (65)	1120** (109)
GasolinePrice(1.5-2.5)*MPG Quart 1	-235* (97)	-1259** (57)
GasolinePrice(1.5-2.5)*MPG Quart 2	-155** (56)	-65 (105)
GasolinePrice(1.5-2.5)*MPG Quart 3	-89* (36)	774** (74)
GasolinePrice(1.5-2.5)*MPG Quart 4	-14 (72)	1065** (113)
GasolinePrice(2.5-3.5)*MPG Quart 1	-239** (79)	-1186** (51)
GasolinePrice(2.5-3.5)*MPG Quart 2	-150** (46)	-48 (90)
GasolinePrice(2.5-3.5)*MPG Quart 3	-63* (29)	682** (59)
GasolinePrice(2.5-3.5)*MPG Quart 4	23 (58)	969** (83)
GasolinePrice(> 3.5)*MPG Quart 1	-399** (71)	-1424** (62)
GasolinePrice(> 3.5)*MPG Quart 2	-118* (46)	-215* (90)
GasolinePrice(> 3.5)*MPG Quart 3	-29 (25)	500** (55)
GasolinePrice(> 3.5)*MPG Quart 4	110* (48)	853** (75)

* significant at 5%; ** significant at 1%; + significant at 10% level. SEs (robust and clustered at the DMA level) in parentheses.
This table only reports the coefficients on gasoline prices.

Table A-12: New Cars: Market share (quartile) results by gasoline price trends†

New Cars Results	MPG Quartile 1	MPG Quartile 2	MPG Quartile 3	MPG Quartile 4
GasolinePrice (3 months up)	-.061** (.0049)	-.015** (.0036)	.0043 (.0034)	.072** (.005)
GasolinePrice (3 months mixed)	-.062** (.0054)	-.015** (.0039)	.0064+ (.0038)	.07** (.0049)
GasolinePrice (3 months down)	-.065** (.0059)	-.017** (.0042)	.0091* (.0044)	.073** (.0053)

* significant at 5%; ** significant at 1%; + significant at 10% level. SEs (robust and clustered at the DMA level) in parentheses.
This table only reports the coefficients on gasoline prices.

Table A-13: New and Used Cars: Price results by gasoline price trends†

	New Cars, MPG Quartiles	Used Cars, MPG Quartiles
GasolinePrice(3 mo up)*MPG Quart 1	-308** (78)	-1189** (46)
GasolinePrice(3 mo up)*MPG Quart 2	-141** (42)	-108 (66)
GasolinePrice(3 mo up)*MPG Quart 3	-53+ (30)	497** (42)
GasolinePrice(3 mo up)*MPG Quart 4	66 (56)	821** (47)
GasolinePrice(3 mo mixed)*MPG Quart 1	-330** (88)	-1276** (51)
GasolinePrice(3 mo mixed)*MPG Quart 2	-167** (46)	-105 (75)
GasolinePrice(3 mo mixed)*MPG Quart 3	-69* (34)	552** (46)
GasolinePrice(3 mo mixed)*MPG Quart 4	51 (64)	923** (52)
GasolinePrice(3 mo down)*MPG Quart 1	-384** (97)	-1401** (59)
GasolinePrice(3 mo down)*MPG Quart 2	-183** (52)	-158* (77)
GasolinePrice(3 mo down)*MPG Quart 3	-92* (38)	585** (50)
GasolinePrice(3 mo down)*MPG Quart 4	42 (69)	1020** (55)

* significant at 5%; ** significant at 1%; + significant at 10% level. SEs (robust and clustered at the DMA level) in parentheses.
This table only reports the coefficients on gasoline prices.

Table A-14: Effect of gasoline price aggregation in market share regression†

	New Cars			
Gas Price Aggregation	MPG Quartile 1	MPG Quartile 2	MPG Quartile 3	MPG Quartile 4
4-digit ZIP	-.044** (.0076)	-.016** (.0039)	.00065 (.0026)	.06** (.0078)
DMA (original specification)	-.057** (.0048)	-.014** (.004)	.0002 (.0027)	.071** (.0058)
PADD	-.059** (.005)	-.013** (.0049)	.00033 (.0032)	.072** (.0058)

* significant at 5%; ** significant at 1%; + significant at 10% level. SEs (robust and clustered at the DMA level) in parentheses.

Table A-15: Effect of gasoline price aggregation in price regression†

Gas Price Aggregation	MPG Quartile 1	MPG Quartile 2	MPG Quartile 3	MPG Quartile 4
New Cars				
4-digit ZIP	-220**	-84**	-7	110*
	(68)	(31)	(28)	(49)
DMA	-250**	-96**	-11	104*
(Base Case)	(72)	(37)	(26)	(47)
PADD	-358**	-88*	34	150**
	(74)	(38)	(30)	(37)
Used Cars				
Gas Price Aggregation	MPG Quartile 1	MPG Quartile 2	MPG Quartile 3	MPG Quartile 4
4-digit ZIP	-1156**	-95	454**	735**
	(46)	(65)	(40)	(46)
DMA	-1182**	-101	468**	763**
(Base Case)	(42)	(62)	(36)	(44)
PADD	-1266**	-121*	524**	859**
	(49)	(58)	(32)	(36)

* significant at 5%; ** significant at 1%; + significant at 10% level. SEs (robust and clustered at the DMA level) in parentheses.

Table A-16: OLS and IV results in market share specification†

	MPG Quartile 1	MPG Quartile 2	MPG Quartile 3	MPG Quartile 4
New Cars				
DMA-level gas prices	-.057**	-.014**	.0002	.071**
OLS (original)	(.0048)	(.004)	(.0027)	(.0058)
PADD-level gas prices	-.059**	-.013**	.00033	.072**
OLS	(.005)	(.0049)	(.0032)	(.0058)
PADD-level gas prices	-.065**	.0024	.0011	.061**
IV	(.0067)	(.0088)	(.0045)	(.011)

* significant at 5%; ** significant at 1%; + significant at 10% level. SEs (robust and clustered at the DMA level) in parentheses.

Table A-17: OLS and IV results in price specification†

	MPG Quartile 1	MPG Quartile 2	MPG Quartile 3	MPG Quartile 4
New Cars				
DMA-level gas prices	-250**	-96**	-11	104*
OLS (original specif.)	(72)	(37)	(26)	(47)
PADD-level gas prices	-358**	-88*	34	150**
OLS	(74)	(38)	(30)	(37)
PADD-level gas prices	-484**	-85**	58**	226**
IV	(24)	(24)	(22)	(20)
Used Cars				
DMA-level gas prices	-1182**	-101	468**	763**
OLS (original specif.)	(42)	(62)	(36)	(44)
PADD-level gas prices	-1266**	-121*	524**	859**
OLS	(49)	(58)	(32)	(36)
PADD-level gas prices	-1751**	-394**	519**	1055**
IV	(23)	(22)	(21)	(22)

* significant at 5%; ** significant at 1%; + significant at 10% level. SEs (robust and clustered at the DMA level) in parentheses.

Table A-18: mlogit estimates (baseline is MPG Quartile 4) †

	New Cars		
	MPG Quartile 1	MPG Quartile 2	MPG Quartile 3
FuelPrice	-.55** (.038)	-.3** (.033)	-.22** (.023)
PctLessHighSchool	.31* (.12)	.27** (.089)	-.034 (.093)
PctCollege	-.52** (.11)	-.15 (.1)	-.19* (.078)
Income	2.3e-06** (7.9e-07)	3.8e-06** (6.7e-07)	3.7e-06** (5.9e-07)
MedianHHSize	.086** (.021)	.044* (.02)	-.01 (.03)
MedianHouseValue	7.4e-07** (2.8e-07)	5.3e-07** (1.9e-07)	4.2e-07** (1.4e-07)
VehiclePerHH	.15 (.18)	.05 (.18)	.31 (.19)
TravelTime	-.004** (.0014)	-.0042** (.00099)	-.0033** (.0009)
Weekend	-.18** (.015)	-.1** (.012)	-.088** (.0092)
EndOfMonth	.054** (.0072)	.045** (.0083)	.056** (.0055)
EndOfYear	-.058** (.021)	-.061** (.02)	-.039+ (.021)
Observations Log pseudolikelihood	1863403 -2483741.3		

* significant at 5%; ** significant at 1%; + significant at 10% level. SEs (clustered at the DMA level) in parentheses.

Table A-19: Regions and DMAs

Baltimore/Washington
Baltimore
Harrisonburg
Richmond-Petersburg
Salisbury
Washington, Dc, Hagerstown

Charlotte
Bluefield-Beckley-Oak Hill
Charleston, SC
Charlotte
Columbia, SC
Florence-Myrtle Beach
Greensboro-H.Point-W.Salem
Greenville-N.Bern-Washngtn
Greenvll-Spart-Ashevll-And
Raleigh-Durham
Tri-Cities, TN-VA
Wilmington

Cincinnati
Charleston-Huntington
Cincinnati
Lexington

Cleveland
Cleveland
Parkersburg
Wheeling-Steubenville
Youngstown

Colorado
Cheyenne-Scottsbluf-Strlng
Colorado Springs-Pueblo
Denver
Grand Junction-Montrose

Columbus
Columbus, OH
Dayton
Lima
Toledo
Zanesville

Dakotas
Billings
Butte-Bozeman
Casper-Riverton
Fargo-Valley City
Glendive
Great Falls
Helena
Minot-Bismarck-Dickinson
Missoula
Rapid City
Sioux City
Sioux Falls(Mitchell)

Detroit
Alpena
Detroit
Flint-Saginaw-Bay City
Grand Rapids-Kalmzoo-B.Crk
Lansing
Traverse City-Cadillac

Georgia
Albany, GA
Atlanta
Augusta
Columbus, GA
Macon
Savannah

Gulf
Alexandria, LA
Anniston
Baton Rouge
Biloxi-Gulfport
Birmingham
Dothan
Hattiesburg-Laurel
Jackson, MS
Lafayette, LA
Lake Charles
Meridian
Mobile-Pensacola
Monroe-El Dorado
Montgomery
New Orleans
Panama City
Tallahassee-Thomasville
Tuscaloosa

Hawaii
Honolulu

Illinois/Indiana
Champaign&Sprngfld-Decatur
Chicago
Davenport-R.Island-Moline
Peoria-Bloomington
Rockford

Indianapolis
Evansville
Ft. Wayne
Indianapolis
Lafayette, IN
Louisville
South Bend-Elkhart
Terre Haute

Kansas City
Kansas City
Lincoln & Hstngs-Krny Plus
North Platte
Omaha
Springfield, MO
St. Joseph
Topeka
Wichita-Hutchinson Plus

Miami
Miami-Ft. Lauderdale
West Palm Beach-Ft. Pierce

Minneapolis
Duluth-Superior
Green Bay-Appleton
La Crosse-Eau Claire
Madison
Mankato
Marquette
Milwaukee
Minneapolis-St. Paul
Rochestr-Mason City-Austin
Wausau-Rhinelander

Missouri
Cedar Rapids-Waterloo&Dubq
Columbia-Jefferson City
Des Moines-Ames
Ottumwa-Kirksville
Paducah-C.Gird-Harbg-Mt VN
Quincy-Hannibal-Keokuk
St. Louis

Nevada
Boise
Idaho Falls-Pocatello
Las Vegas
Reno
Salt Lake City
Twin Falls

New England
Bangor
Boston
Burlington-Plattsburgh
Portland-Auburn
Presque Isle
Providence-New Bedford
Springfield-Holyoke

New York
Albany-Schenectady-Troy
Binghamton
Elmira
Hartford & New Haven
New York
Rochester, NY
Syracuse
Utica
Watertown

Norfolk/Virginia Beach
Charlottesville
Norfolk-Portsmth-Newpt Nws
Roanoke-Lynchburg

Northern California
Chico-Redding
Eureka
Fresno-Visalia
Monterey-Salinas
Sacramnto-Stkton-Modesto
San Francisco-Oak-San Jose

Oklahoma
Amarillo
Ft. Smith-Fay-Sprngdl-Rgrs
Joplin-Pittsburg
Oklahoma City
Tulsa
Wichita Falls & Lawton

Orlando
Gainesville
Jacksonville, Brunswick
Orlando-Daytona Bch-Melbrn

Pennsylvania
Harrisburg-Lncstr-Leb-York
Philadelphia
Wilkes Barre-Scranton

Phoenix
Albuquerque-Santa Fe
Phoenix
Tucson(Nogales)

Pittsburgh
Buffalo
Clarksburg-Weston
Erie
Johnstown-Altoona
Pittsburgh

San Antonio
Harlingen-Wslco-Brnsvl-Mca
Laredo
San Angelo
San Antonio

Seattle/Portland
Bend, OR
Eugene
Medford-Klamath Falls
Portland, OR
Seattle-Tacoma
Spokane
Yakima-Pasco-Rchlnd-Knnwck

South Texas
Austin
Beaumont-Port Arthur
Corpus Christi
Houston
Victoria

Southern California
Bakersfield
Los Angeles
Palm Springs
San Diego
SantaBarbra-SanMar-SanLuOb
Yuma-El Centro

Tampa
Ft. Myers-Naples
Tampa-St. Pete,Sarasota

Tennessee
Bowling Green
Chattanooga
Columbus-Tupelo-West Point
Greenwood-Greenville
Huntsville-Decatur,Flor
Jackson, TN
Jonesboro
Knoxville
Memphis
Nashville

Texas
Abilene-Sweetwater
Dallas-Ft. Worth
El Paso
Little Rock-Pine Bluff
Lubbock
Odessa-Midland
Sherman-Ada
Shreveport
Tyler-Longview(Lfkn&Ncgd)
Waco-Temple-Bryan